ITIKI:

Bridge between African Indigenous Knowledge and Modern Science on Drought Prediction

By

Euphraith Muthoni Masinde

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Dr Antoine Bagula

and

Prof. Nzioka Muthama

Dedication

It is with great joy that I dedicate this work to my beloved husband, Wanyama Masinde; no amount of words can express how grateful I am for all the support you gave me while I was pursuing this research.

To my lovely children; Imani, Baraka, Neema and Pendo: thank you for accepting to make do with less of Mummy when I had to stay in Cape Town for weeks and even when I had to sit at my reading desk instead of attending to you.

To my late dad, Ireri: I sincerely owe this to you; while I was still a small girl, you planted the seed of dedication, determination and hard work in me.

--Muthoni

Declaration

This thesis is a presentation of my original research work. Wherever contributions of other people are involved, every effort has been made to indicate this clearly, with due reference to the literature and acknowledgement. Further, this work was done under the guidance of Dr Antoine Bugula, Department of Computer Science, University of Cape Town and Professor Nzioka Muthama, Department of Meteorology, University of Nairobi.

Euphraith Muthoni Masinde

Date: ___________________________________

Signature: _______________________________

In our capacity as supervisors of this thesis, we certify that the above statements are true to the best of our knowledge

Dr Antoine Bagula

Date: ___________________________________

Signature: _______________________________

Prof. Nzioka Muthama

Date: ___________________________________

Signature: _______________________________

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Abstract

The now more rampant and severe droughts have become synonymous with Sub-Saharan Africa; they are a major contributor to the acute food insecurity in the Region. Though this scenario may be replicated in other regions in the globe, the uniqueness of the problem in Sub-Saharan Africa is to be found in the ineffectiveness of the drought monitoring and predicting tools in use in these countries. Here, resource-challenged National Meteorological Services are tasked with drought-monitoring responsibility. The main form of forecasts is the Seasonal Climate Forecasts whose utilisation by small-scale farmers is below par; they instead consult their Indigenous Knowledge Forecasts. This is partly because the earlier are too supply-driven, too 'coarse' to have meaning at the local level and their dissemination channels are ineffective.

Indigenous Knowledge Forecasts are under serious threat from events such as climate variations and 'modernisation'; blending it with the scientific forecasts can mitigate some of this. Conversely, incorporating Indigenous Knowledge Forecasts into the Seasonal Climate Forecasts will improve its relevance (cultural and local) and acceptability, hence boosting its utilisation among small-scale farmers. The advantages of such a mutual symbiosis relationship between these two forecasting systems can be accelerated using ICTs. This is the thrust of this research: a novel drought-monitoring and predicting solution that is designed to work within the unique context of small-scale farmers in Sub-Saharan Africa. The research started off by designing a novel integration framework that creates the much-needed bridge (***itiki***) between Indigenous Knowledge Forecasts and Seasonal Climate Forecasts. The Framework was then converted into a sustainable, relevant and acceptable Drought Early Warning System prototype that uses mobile phones as input/output devices and wireless sensor-based weather meters to complement the weather stations. This was then deployed in Mbeere and Bunyore regions in Kenya.

The complexity of the resulting system was enormous and to ensure that these myriad parts worked together, artificial intelligence technologies were employed: artificial neural networks to develop forecast models with accuracies of 70% to 98% for lead-times of 1 day to 4 years; fuzzy logic to store and manipulate the holistic indigenous knowledge; and intelligent agents for linking the prototype modules.

Extended Abstract

The now more rampant and severe droughts have become synonymous with the Sub-Saharan Africa where they are a major contributor to the acute food insecurity in the Region. Though this is not different from other regions in the world, the uniqueness of the problem in the Sub-Saharan Africa countries is the ineffectiveness of the drought monitoring and predicting tools in use in these countries. Accurate and reliable drought forecasts, when delivered in a timely fashion and in formats that are comprehensible to the targeted users, are a precursor to successful drought mitigation strategies. There is a link between weather monitoring and droughts; accurate weather monitoring can detect droughts occurrence long before they strike. In Sub-Saharan Africa, resource-challenged National Meteorological Services are tasked with this responsibility. Although these Services use well-calibrated weather stations that meet World Meteorological Organisation's standards, the high cost of acquiring the stations allows only a sparse deployment.

Despite this challenge, these institutions continue to provide regular climate forecasts especially in form of Seasonal Climate Forecasts. The utilisation of these forecasts by the small-scale farmers whose crops/livestock depend solely on rainfall is still very low; they instead continue to consult their Indigenous Knowledge Forecasts for their cropping decisions. This is partly because the Seasonal Climate Forecasts are too supply-driven, too 'coarse' to have meaning at the local level and the dissemination channels are ineffective. Why small-scale farmers? Economies of most countries in the Sub-Saharan Africa are agri-based with over 70% of food being produced by small-scale farmers practicing rain-fed agriculture. The latter in extremely responsive to weather patterns and a good rain season translates to bumper harvest and hunger and despair otherwise.

Though the holistic Indigenous Knowledge Forecasts that these farmers have relied on since time immemorial has always worked, there is evidence that the knowledge is under serious threat from events such as climate change and 'modernisation'. Some of these threats can be countered by blending it with the Seasonal Climate Forecasts. On the other hand, incorporating Indigenous Knowledge Forecasts into the Seasonal Climate Forecasts will improve its relevance (both locally and culturally) and acceptability and hence boost their utilisation among the small-scale farmers.

The advantages of this mutual symbiosis relationship between the two forecasting systems have been recognised and pursued in a few initiatives, but with little success. The main challenge is the inability of these initiatives to scale-up beyond a region/community and two, the lack of micro-level weather data to validate the forecast outcomes. Information and Communication Technologies (ICTs) can

accelerate this integration; this is the focus of this research. The thesis describes a novel drought monitoring and predicting solution that is designed to work within the unique context of small-scale farmers in Sub-Saharan Africa. The research started off by designing a unique integration framework that creates the much-needed ***bridge (itiki)*** between Indigenous Knowledge Forecasts and Seasonal Climate Forecasts. The Framework was then converted into a Drought Early Warning System prototype made up of three components; (1) Drought Knowledge; (2) Drought Monitoring and Prediction; and (3) Drought Dissemination and Communication. To achieve sustainability, relevance and acceptability, indigenous knowledge was integrated in each of the three components while mobile phones were used as both input and output devices for the system. In order to facilitate collection and conservation of indigenous knowledge on drought monitoring, an elaborate Android-based mobile application was developed while text-to-speech and speech-to-text plug-ins were incorporated to cater for semi-illiterate farmers. Wireless sensor-based weather meters were acquired, calibrated against conventional weather stations and deployed as a compliment to the weather stations. This proved the hypothesis that, when deployed in hundreds, these sensors are capable of extending the weather network coverage to enhance weather forecasting by downscaling the reading of weather parameters to tens of meters.

Weather data is a 'gold mine' for many sectors of an economy and to allow public access to drought monitoring system data, a comprehensive web portal and an SMS-based component were also implemented. In order to collect real data for the indigenous drought forecast aspect, a case study of two communities in Kenya (Mbeere and Bunyore) was carried out. On completion of the system prototype, participants from the two communities evaluated it; based on content and format of the integrated forecasts, 90% of respondents gave a score of 'excellent'.

The complexity of the resulting system was enormous and to ensure that the above diverse parts worked together, artificial intelligence technologies were heavily used in developing the system. Artificial Neural Networks were used to develop forecast models whose accuracies ranged between 75 and 98% for lead-times of one day to four years. Fuzzy logic was used to store and manipulate the holistic indigenous knowledge while intelligent agents were used to integrate all the sub-systems into a single unit. After evaluating it using over forty years of historical weather data from Kenya, Effective Drought Index was adopted for drought monitoring because of its ability to quantify and qualify drought in absolute terms.

List of Acronyms

AI	Artificial Intelligence
ANFIS	Adaptive Neural Network-based Fuzzy Inference System
ANNs	Artificial Neural Networks
AWRI	Available Water Resources Index
BDI	Belief, Desire and Intention
DEWS	Drought Early Warning System
DFAS	Drought Forecast and Alert System
DMSNN	Direct Multi-Step Neural Network
EAC	East African Community
EDI	Effective Drought Index
EW	Early warning
FAO	Food and Agriculture Organisation
FEWS-Net	Famine Early Warning System Network
FMF	Fuzzy Membership Function
GIEWS	Global Information and Early Warning System on Food and Agriculture
GMT	Greenwich Mean Time
GSM	Global System for Mobile
GPRS	General Packet Radio Service
HEWS	Humanitarian Early Warning Service
HPI	Hasso-Plattner Institut
ICAO	International Civil Aviation Organisation
ICT4D	Information Communication Technologies for Development
ICTs	Information Communication Technologies
IDE	Integrated Development Environment
IK	Indigenous Knowledge
IKFs	Indigenous Knowledge Forecasts
IRMA	Intelligent Resource-bound Machine Architecture
ITIKI	Information Technology and Indigenous Knowledge with Intelligence
ITU	International Telecommunication Union
IVR	Interactive Voice Response
JADE	Java Agent Development

KMD	Kenya Meteorological Department
MAM	March-April-May
MAPE	Mean Absolute percentage Error
ME	Mean Error
MobiGrid	Mobile Phone Grid
MobiSoc	Mobile Phone Service Oriented Computing
MODIS	Moderate Resolution Imaging Spectroradiometer
NMSs	National Meteorological Services
OND	October-November-December
PiECEs	Pilot, Exploratory and Confirmatory Experiments
PRS	Procedural Reasoning System
RMSE	Root Mean Square Error
RMSNN	Recursive Multi-Step Neural Network
RPC	Recursive Participatory Experiments
SCFs	Seasonal Climate Forecasts
SMS	Short Message Service
SPATSIM	Spatial and Time Series Information Modelling
SPI	Standard Precipitation Index
SSA	Sub-Saharan Africa
UCT	University of Cape Town
WFP	World Food Programme
WMO	World Meteorological Organisation
WSNs	Wireless Sensor Networks

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1 Introduction and Background Information

1.0 Problem Statement

There is a complex link between droughts and development (or lack of it); in most African countries, rain-fed agriculture accounts for over 70% of food production (ISDR, ECA et al. 2008). This form of agriculture is extremely responsive to weather and when droughts strike, millions go hungry (Virji, Cory et al. 1997). Hungry people do not think of anything beyond the next meal and therefore, all developmental issues take a back seat during such times (World Food Programme 2006). In the face of droughts, governments are forced to re-direct budgets initially allocated for developmental projects towards supporting the hungry (Mutua 2011).

Effective drought early warning systems (DEWS) have high potential in making a contribution towards tackling the cycle of droughts. This is by way of providing timely, relevant and comprehensible information on impending droughts that could be used to mitigate droughts' effects and therefore reduce their negative impacts on the fauna and flora. Successful DEWS in turn rely on weather forecasting systems in place. Implementation of weather forecasting systems in many African countries is hampered by among other things, inadequate coverage by weather stations. The second challenge of weather forecasting emanates from very poor utilisation of the Seasonal Climate Forecasts (SCFs) by the very farmers that grow the food for the masses. The content, format and dissemination channels used do not address the farmers' needs; the farmers have in turn continued to rely on their indigenous knowledge forecasts (IKFs) to derive critical cropping decisions (Mugabe, Mubaya, Nanja et al. 2010; Ziervogel, Bithell et al. 2005). Though being very rich and relevant to the farmers' context, there is evidence that IKFs are an endangered species in dire need of conservation and revamping (Roncoli 2006; Orlove, Carla et al. 2009). Further, apart from the fact that DEWS are the most complex of all early warning systems (Grasso 2007), an attempt to have both IKFs and SCFs in one system would increase this complexity exponentially.

One of the major weaknesses of the existing drought prediction tools is the emphasis on macro/international level information. Further, the design and implementation of drought communication strategies tend to ignore the 'at risk' community who also happen to be host to very crucial indigenous knowledge on drought, their environment and indigenous coping mechanisms. In Sub-Saharan

Africa, early warning systems that attempt to address droughts are multi-hazard with drought being just a small component of the entire system. To compound this problem, the existing solutions are faced with a number implementation challenges and the utilisation of their output is very low. Utilisation of the disseminated information by key stakeholders such as small-scale farmers is fraught with numerous challenges emanating from their unreliability (real and perceived) and their 'course' nature that makes them irrelevant at the local (say a village) level.

Researchers and practitioners alike have identified Information and Communication Technologies (ICTs) as a critical catalyst for accelerating development in the developing countries of Africa (Chapman, Tom 2002). This thesis describes research which is a novel contribution to this end; a home-grown drought monitoring and forecasting solution build around three ICTs: mobile phones, wireless sensor networks (WSNs) and artificial intelligence (AI).

1.1 Motivation and Justification

The frequency, magnitude and duration of natural disasters triggered by climate variations are on the rise globally, thanks to events such as climate change, global warming and population growth. Droughts continue to affect millions of people in Africa; according to the World Disasters Report of 2011, Africa contributed over 50% of the droughts that occurred in the world between 2001 and 2011. Most of these occurred in the Sub-Saharan Africa (SSA) (Armstrong, Mark et al. 2011). The uniqueness of the problem in SSA however, is to be found in the inadequacy and ineffectiveness of the Region's preparedness to these disasters (Patt, Jordan, 2007; Masinde, Bagula et al. 2012a). Further, most economies in SSA are driven by the notoriously climate-sensitive agriculture sector and as Virji et al. (1997) put *it: "...agricultural production and weather are so highly interrelated that a good rainy season means a healthy economy, and failure of the rains ... means famine and death" (pg 8)*. Further: *"Of the ten countries with the highest levels of hunger, and of the ten whose scores have actually increased since 1990, nine are in Sub-Saharan Africa in both cases"* (IFPRI 2011).

Information is power and ensuring that the local communities have access to tailor-made information on impending droughts is one way of giving them power to protect themselves from their negative effects. Despite the challenging contexts they operate in, meteorological institutions in SSA continue to provide regular climate forecasts especially in form of Seasonal Climate Forecasts (SCFs). However, the utilisation of this information by the small-scale farmers whose crops/livestock depend solely on rainfall is still below par (Ziervogel, Calder 2003; and Ziervogel, Bithell et al. 2005). Studies (Luseno, McPeak et al. 2003; and Mugabe, Mubaya, Nanja et al. 2010) reveal that over 80% of farmers in some parts of Ethiopia, Kenya, Zambia and Zimbabwe relied on IKFs. However, IKFs are currently facing challenges from various quarters especially from climate change, urbanisation and population growth.

There are renewed efforts towards promoting IKFs especially on disaster management and how to integrate them to the SCFs (Stigter, Zheng et al. 2005; Ziervogel, Bithell et al. 2005; Roncoli 2006; Mercer, Kelman et al. 2010). This is driven by the realisation that SCFs and IKFs complement each other and that the rich IKFs could help in making the forecasts more relevant to the local people's context. Though having generated promising results, such integration initiatives still face the challenges of scaling up beyond small communities/villages and scaling down in terms of availing localised weather data. Innovative use of the readily available mobile phones and the versatile wireless sensor networks technology can be used to address these two challenges and hence accelerate these success stories. Further, adoption of selected intelligent algorithms could ease the process of this rather complicated integration. Growth in mobile phones subscription and usage in developing countries is phenomenal. By 2011 for example, Africa had a mobile cellular subscriptions of 433 million (ITU 2011); though still the lowest among all the continents, Africa registered the highest subscriptions growth during this period. Given that this penetration is much higher than any other forms of ICTs, these phones offer a ray of hope for the African countries if only scientists could come up with relevant mobile phone-based applications that can be used to negate effects of droughts.

1.2 Hypothesis

This research was guided by the hypothesis that people-centred drought early warning systems can empower people at the local level. Such systems increase people's sense of ownership and confidence in using the systems. Consequently, the people become more resilient to the droughts and are able to protect themselves. In the African context, one way of achieving this is by incorporating African indigenous knowledge on droughts, exploiting the widely available mobile phones and employing Wireless Sensor Networks (WSNs) to collect micro/local droughts data.

1.3 The Solution

To address the problem stated in section 1.2, we developed a novel ***bridge*** dubbed ***itiki*** that delivers a drought early warning system (DEWS) composed of three elements: (1) Drought Knowledge (2) Drought Monitoring and Prediction; and (3) Drought Communication and Dissemination. ITIKI; acronym for ***I****nformation* ***T****echnology and* ***I****ndigenous* ***K****nowledge* with **I***ntelligence* is a bridge that integrates indigenous drought forecasting approach into the scientific drought forecasting approach. ITIKI was conceptualised from ***itiki*** which is the name used among the Mbeere people (found in the Eastern part of Kenya), to refer to an indigenous bridge made using sticks and was used for decades to go across rivers. Until mid 90s, this bridge used to be constructed by 'experts' who possessed indigenous knowledge on the rivers' terrain as well as on the strength of the various trees along the rivers and the trees' ability to sustain the weight that the bridge would eventually carry. Such was the accuracy of this knowledge that during the 1992 floods, a newly constructed modern bridge was swept away while the ***itiki*** nearby was left standing (witnessed by the author). To tackle the diverse characteristics of these two knowledge systems, ITIKI is hinged on three ICTs: (1) mobile phones; (2) Wireless sensor networks; (3) Artificial Intelligence (agents, fuzzy logic and artificial neural networks). This thesis is a documentation of the entire process we undertook in building ITIKI; starting from its conceptualisation to deployment and evaluation.

1.3.1 Research Questions

The research was guided by the following research questions:

i. Does the incorporation of indigenous knowledge into a drought prediction tool improve the tool's resilience and relevance to the countries in Sub-Saharan Africa?

ii. How can the readily available mobile phones' computational power that lay idle (most of the times) be harnessed and integrated with Wireless Sensor Networks and be used in developing an affordable and sustainable drought prediction tool for Sub-Saharan Africa countries?

1.3.2 Research Objectives

The main objective of this research was to develop an effective, sustainable and relevant 'home-grown' Drought Early Warning System (DEWS) for the Sub-Saharan Africa by making use of Artificial Intelligence technologies to integrate; indigenous knowledge on droughts, scientific weather forecasts, Wireless Sensor Networks (WSNs) and mobile phones.

This was achieved through the following specific objectives:

i. to investigate the suitability and field readiness of Wireless Sensor Networks WSNs) in weather monitoring;

ii. to investigate the feasibility of extending the functionality of mobile phones into computing devices that can handle some aspects of drought forecasting;

iii. to evaluate the strengths of Effective Drought Index (EDI) as a tool for monitoring droughts in terms of their severity, onset, cessation and probability of their occurrence;

iv. to design and implement a system that makes use of mobile phones to document and conserve indigenous knowledge on droughts;

v. to design and develop intelligent computer algorithm(s) that integrates Indigenous Knowledge on droughts, weather data read by wireless sensors and other local/regional/global weather patterns observed from weather stations. This is for the purpose of predicting droughts at micro levels (such as a village);

vi. to apply (i) to (v) above in the design and development of an affordable and relevant drought forecasting solution for use in the countries within the Sub-Saharan Africa;

vii. to evaluate the success of the above using various benchmarks;

viii. to document the findings in a PhD thesis.

1.4 Research Achievements and Contribution

The main contribution of this research is a framework for drought prediction that creates the missing link (bridge) between the scientific and indigenous drought forecasting systems. In contrast to conventional drought prediction systems that tend to provide macro-level drought parameters and are based on expensive sensing equipment and satellite systems for information dissemination, our framework makes use of the more cost effective off-the-shelf wireless sensor network technology to complement the expensive and sparse network of weather stations. We also used the now prevalent mobile phones to disseminate micro-level drought information in formats and semantics that are relevant to the users at the grassroots, especially small-scale farmers.

In order to make the solution relevant to Sub-Saharan Africa, the framework integrates indigenous knowledge on droughts as a prediction variable. To further improve its relevance, acceptability and resilience, the framework was designed in consultation with representatives from two communities in Kenya. For the actual drought prediction, three Artificial Intelligence techniques (Agents, Artificial Neural Networks and Fuzzy Logic) were adopted for situation recognition. Systematic approach to the design of the integrated tool was followed; this ensured that the tool is generic and can be ported not only across communities and regions but also across other domains such as Monitoring Climate Change. In order to test the framework, an integrated system prototype was developed and deployed and is accessible to members of public via a user-friendly web portal and can also be interrogated by sending text messages from mobile phones.

In finer detail, this research produced the following novel contributions:

Being a relatively new technology in Africa, the use of wireless sensor networks for weather monitoring is still an unexplored territory. This research ventured into this by first identifying appropriate sensor boards for weather monitoring and went a step further to calibrate these sensors against conventional weather stations. The sensors were then deployed for weather monitoring in selected locations in Kenya.

Secondly, the two most commonly used drought indices in the SSA countries are El Nino–Southern Oscillation (ENSO) and North Atlantic Oscillation (NAO). These two only forecast medium-term droughts and they do not give the severity of the drought. Part of the output from our research is a drought-forecasting component that combines the use of Artificial Neural Networks (ANNs) and Effective Drought Index (EDI) to forecast drought for periods ranging from one day to four years with accuracies ranging from 75% to 98%. This is a phenomenal improvement on the accuracy (most existing solutions' accuracy is about 70%) of the forecasts. Further by adopting EDI, it is now possible to map droughts day-by-day in five in dimensions; (1) onset; (2) severity; (3) duration; (4) cessation; (5) probability of future occurrence. We demonstrated this using historical weather data for Kenya. Though the integration of EDI and ANNs has been attempted elsewhere in the world especially in South-East Asia, no research known to us has attempted to model the micro (daily) level of details like it has been done in this research.

Thirdly, the critical role of indigenous knowledge on drought forecasting in building relevant, resilient and effective drought early warning systems has been taken a notch higher in this research. We have demonstrated how the use of fuzzy logic to model indigenous knowledge is not only a better way of conserving the holism of this knowledge but also a step towards integrating it with the scientific drought forecasting systems. The available literature on modelling of indigenous knowledge (which is mostly on classifying soil types) using fuzzy logic and how this can be integrated to its scientific counterpart was reviewed; none was found to tackle the very complex domain of indigenous knowledge on weather and droughts. To this end, this aspect of our research is a unique contribution to the body of knowledge.

Fourth, the use of mobile phones both at the '*first-mile'* and the *'last-mile'* of the drought early warning system were adopted in this research; the unique contribution here is that the research extended the use of mobile phone beyond its conventional use into a computing device. This was achieved through a novel middleware (MobiGrid, Masinde, Bagula et al. 2010) that allows a pool of phones to operate in a grid version. To further improve the use of this grid, a service oriented interface that allows applications to run on MobiGrid as a service was developed (MobiSOC, Masinde, Zebal et al. 2012). Though still at prototyping stages, these again were unique contributions to the world of mobile computing.

The juggling of the myriad elements that were integral part of this research forced the authors to 'think outside the box' when it came to choosing from among the existing research methodologies and design. During the implementation of the Experimental Research Design a novel approach called *Recursive Participatory*

Experiments (RPE) was born; the details of this are in Chapter 3. Finally, an elaborate system prototype was a major deliverable of this research; this provides the sneak-peak through which the outside world can test some of our research outputs. This is a comprehensive system made up of several sub-systems that are linked up together by intelligent agents that were implemented using the Java-based multi-agent systems' development framework called JADE (Java Agent Development). The sub-systems are: (1) Sensor-Based Weather Monitoring System prototype; (2) The EDI Monitor which is a FORTRAN program; (3) ANNs Forecasting Tool; (4) IK Fuzzy Sub-System that stores Indigenous Knowledge (IK) drought indicators; (5) Android Mobile Application to input and output IK indicators as well extreme weather events; (6) SMS Gateway that allows members of the public to interact with the entire system and also used to receive weather readings from sensors into the system; and (7) a user-friendly web portal used for both system administration as well for displaying detailed information on droughts and other related details.

1.5 Research Evaluation Criteria

In line with the objectives set out under section 1.3.2, this research was evaluated as follows:

In order to assess the relevance of using off-the-shelf sensor technology in weather forecasting, calibration of the selected weather sensors was carried out using conventional weather stations at the Kenya Meteorological Department. Using the Mean Absolute Percentage Error and Root Mean Square Error metrics, the weather sensors gave accuracies of 92 to 99%.

On the objective of extending the functionality of mobile phones into computing devices, we developed a mobile phone based middleware called MobiGrid that supports grid computing on mobile phones. To support service-oriented computing, MobiGrid was further extended MobiGrid into MobiSoc. MobiGrid Lite was later developed to address some shortcomings of MobiGrid (Masinde, Bagula et al. 2010; Masinde, Zebal et al. 2012).

After reviewing the most commonly used drought indices, daily weather data for over 30 years from four weather stations in Kenya was used to evaluate the strengths of the Effective Drought Index (EDI). We demonstrate that EDI is able to quantify and qualify past droughts day-by-day in five dimensions; (1) onset; (2) severity; (3) duration; (4) cessation; (5) probability of future occurrence.

Given the complexity of the art of drought prediction, we incorporated the use of three Artificial Intelligence techniques to manage this as well as handle the holistic indigenous knowledge. Artificial Neural Networks (ANNs) approach was excellent in solving the data-intensive and multivariable aspect of drought forecasting while Fuzzy Logic was adopted in representing IK indicators on drought. Intelligent Agents helped in tying all the sub-systems into one integrated intelligent system.

After designing a robust back-end database for storing IK on droughts, an Android application was developed and deployed on Huawei's IDEOS handset that retailed at approximately USD 100 at the time of deploying the system. For sustainability purposes, the application was designed to work around focus groups led by an IK Experts' intermediary who is responsible for sending the IK indicators using the phone.

After deploying the integrated system, the use of the system by selected groups of users from Mbeere and Bunyore in Kenya was monitored. Guided interviews and system demonstration were then used to evaluate the extent to which the system met farmers' needs for accurate, relevant, useable and timely weather and drought information. These were then analysed in relation to the existing weather monitoring and forecasting system currently managed by the Kenya Meteorological Department.

1.6 Thesis Structure

The structure of the thesis is guided by the components that make up ITIKI; each component (except for component 2 which was split into Chapter 6 and 7) taking a chapter. In modelling IK on weather/droughts, two regions in Kenya: Bunyore and Mbeere, were selected for testing and evaluating ITIKI. While Bunyore was selected because a related initiative (integrating IKFs with SFCs) had been piloted there, Mbeere was picked because of the author's familiarity with the region having lived there for over 20 years. Below is the detailed structure of the thesis.

Chapter 2 – Literature Review: This is a detailed review of the relevant (to this research) literature. This includes a detailed study of droughts in terms of definitions, their complex nature/cost, drought indices, and how ICTs (Mobile phones, wireless sensor networks and artificial intelligence) can be used to tackle them. A brief overview of Artificial Intelligence techniques is presented followed by detailed description of three of these techniques (Agents, Artificial Neural Networks and Fuzzy Logic) that have been employed in this research to develop an early warning system for droughts. There is a close link between climate/weather forecasting and drought prediction and therefore this chapter also includes a thorough study of both indigenous and modern sciences of weather forecasting. The final part of this chapter is a brief introduction to drought early warning systems.

Chapter 3 – Research Methodology and Design: The chapter describes the research methods and designs that were used in the course of this research.

Chapter 4 – ITIKI Architecture: This is where the various components of the Drought Early Warning System are described and the system's architecture presented. In particular, the unique role of the selected ICTs in the entire system is described and also how the various components contribute towards the overall object of the entire research is presented.

Chapter 5 – Collecting Drought Risk Knowledge: This chapter is dedicated to the discussion on the first component of the ITIKI. It gives the details on how both structure and unstructured data and knowledge on droughts is harvested from the three sources: manually operated weather stations, wireless sensors-based weather meters and indigenous knowledge experts. .

Chapter 6 – Drought Monitoring Using EDI: This chapter handles the first sub-component of 'Drought Monitoring and Prediction' element of ITIKI. It describes how the Effective Drought Index (EDI) was employed to monitor droughts.

Chapter 7 – Drought Prediction using ANNs: This takes care of the second sub-component of 'Drought Monitoring and Prediction' element of ITIKI. It describes in details the drought-forecasting tool that was developed using Artificial Neural Networks. This tool gives EDI and AWRI values as output and forecasts droughts for various timescales such as daily, weekly, monthly, half-year, one year, two years, up to four years.

Chapter 8 – Drought Communication and Dissemination: This implements the third component of ITIKI. Since it involves communication with the outside world the users, this chapter is basically the description of the implementation of ITIKI's logic and its various interfaces for input and output. It is here that the sub-systems discussed in Chapters 5, 6 and 7 are integrated into one system; this is achieved using Multi-Agent System (MAS) as implemented in JADE.

Chapter 9 – Evaluation Discussion and Further Work: The evaluation of ITIKI is presented in this chapter. A detailed discussion of the findings and proposed further work is also presented here.

2 Literature Review

2.0 Introduction

This chapter is a thorough review of literature that informed the various decision reached in this study. The first part is a detailed study of droughts in terms of definitions, their complex nature/cost, drought indices, and how ICTs (Mobile phones, wireless sensor networks and artificial intelligence) can be used to tackle them. A brief overview of Artificial Intelligence techniques is presented followed by detailed description of three of these techniques (Agents, Artificial Neural Networks and Fuzzy Logic) that have been employed in this research to develop an early warning system for droughts. There is a close link between climate/weather forecasting and drought prediction and therefore this chapter also includes a thorough study of both indigenous and modern sciences of weather forecasting. Apart from examples of indigenous parameters/indicators used for climate/weather forecasting, a comparison of both sciences is also presented. A detailed study of how modern seasonal climate forecasts (SCFs) are derived is also described, and finally a description of some frameworks that attempt to integrate the two. The final part of this chapter is a brief introduction to drought early warning systems.

2.1 Droughts

2.1.1 Drought Definitions

Drought is an insidious hazard of nature which according to Elsa, Carlos et al. (2008), qualifies as a hazard because it is a natural accident of unpredictable occurrence but of recognizable recurrence and as a disaster, it corresponds to the failure of the precipitation regime, causing the disruption of the water supply to the natural and agricultural ecosystems. There is no one universally accepted definition of drought yet. Palmer came to this conclusion as early as 1965 when he stated "*Drought means various things to various people depending on their specific interest. To the farmer drought means a shortage of moisture in the root zone of his crops. To the hydrologist, it suggests below average water levels in the streams, lakes, reservoirs, and the like. To the economist, it means a shortage which affects the established economy*" (Palmer 1965). Since then, attempts have been made to define the term drought. In Mishra, Singh (2010), the definitions are classified under two categories: (1) **Conceptual definitions** that define drought in relative terms such 'a long dry period'; such definitions help people to contextualize droughts. For example "*protracted period of deficient precipitation resulting in extensive damage to crops, resulting in loss of yield"* (http://flood.unl.edu/web/drought/whatisdrought). In Kung, Hua et al. (2006) and Kim, Hi-Ryong et al. (2009) the following contextualised (related to Taiwan) drought definitions are described: (1) Rainless day with rainfall less than 0.6cm; (2) small-scale drought without rainfall lasting 50 days; (3) large-scale drought without rainfall for over 100 days; and (2) **Operational definitions**, on the other hand, identify the onset, severity and termination of drought.

Examples of Working Definitions: The following international organisations came up with working definitions that are specific to the nature of the work in which they are involved: *The World Meteorological Organisation* – "drought is a sustained, extended deficiency in precipitation" (World Meteorological Organisation (WMO) 1986); *The UN Convention to Combat Drought and Desertification* – "drought is the naturally occurring phenomenon that exists when precipitation has been significantly below normal recorded levels, causing serious hydrological imbalances that adversely affect land resource production systems" (UN Secretariat General 1994); and *The Food and Agricultural Organisation* – "drought is the percentage of years when crops fail from lack of moisture: (Food and Agricultural Organisation (FAO) 1983).

Warwick (1975) defined drought "*as a condition of moisture deficit sufficient to have an adverse effect on vegetation, animal and man over a sizeable area*". As in the definition given by Wilhite, Glantz (1985) and Dracup, Kil et al. (1980), Warwick's definition implies three categories of drought: **Meteorological**: A period of abnormally dry weather sufficiently prolonged for the lack of water/rainfall to cause serious hydrologic imbalance in the affected area (Huschke 1959); **Hydrological**: A period of below average water content in streams, reservoirs, groundwater aquifers, lakes and soils (Yevjevich, Hall et al. 1977); and **Agricultural**: Climatic excursions involving a shortage of precipitation sufficient to adversely affect crop production or range of production (Rosenberg 1979); the latter is a manifestation of meteorological and hydrological droughts. Two other categories of drought that are a result of these three that have been proposed by researchers whose work is referenced in Mishra, Singh (2010) are: **Social-economic Drought**, which occurs when the demand for an economic good exceeds supply as a result of weather-related shortfall in water supply and **Ground Water Drought**, which is the decrease in ground water discharge and levels.

2.1.2 What Causes Droughts?

Droughts are multi-faceted and may be contributed to by both natural and human factors. The natural factors include temperatures, winds, relative humidity and rainfall. Deforestation and overexploitation of water sources are the two main human factors that trigger droughts. A necessary and sufficient condition for any form of drought is therefore below-'normal' precipitation which can be caused by an array of natural factors such as over-seeding of clouds by dust particles from the earth's surface, an increase in albedo[1], a decrease in the availability of biogenic nuclei for raindrop formation caused by reduced plant cover and similar factors. Droughts are also caused by oceanic circulations patterns (pressure and anticyclonic) that affect current and heat storage. One interesting relationship among these variables is that below-'normal' precipitation/rainfall is the chief causative parameter of drought; soil moisture (responds to precipitation anomalies on a relatively short time-scale), stream-flow, reservoir storage and groundwater level are the main parameters reflecting drought impacts.

Among other things, drought prediction plays a critical role in the planning and management of the now scarce water resource. Parametric indicators of drought commonly computed are: (1) duration; (2) severity; (3) location of the drought in absolute time (initial and termination time points); (4) area of the drought coverage; (5) magnitude/density of the drought computed by getting the ratio of severity to duration (Panu, Sharma 2002). Byun, Wilhite (1999) categorised research in the topic on droughts under studies aimed at: (1) understanding the causes of droughts; (2) looking at the frequencies and severity of droughts; (3) describing and understanding of the impacts of droughts; (4) looking at responses, appropriate mitigation, and preparedness strategies; this focuses on a reduction of the impacts associated with drought. Though our research looks at all of these, more focus was on categories (2) and (4).

2.1.3 Impacts, Cost and Complexity of Droughts

Droughts are among the most expensive disasters in the world, the negative impacts of which span economic, social and environmental aspects of the affected society. It is even more difficult to quantify the cost of droughts because most of the effects are indirect. Some direct ones include: effects on human/animals; decline in food yield, forest and greenbelt; worsening water/air quality and sanitation; and higher fire prevention risk. Indirect effects include: price upsurge; reduction of income; loss of jobs; and degradation of living standards among others (Kung, Hua et al. 2006).

Droughts accounted for 50% of the 2.8 billion people affected by natural disasters between 1967 and 1992 (Mishra, Desai 2006). The study by Mishra, Singh (2010) showed that among all the natural disasters, droughts have the most impact on a country's economy. The US, for example,

[1] Albedo is defined as the ratio of total-reflected to incident electromagnetic radiation. It is a unitless measure indicative of a surface's or body's diffuse reflectivity; http://en.wikipedia.org/wiki/Albedo

spent $40 billion to counter the 1988 drought, while floods a year later cost the government 2-3 times less. Among the natural disasters that faced the US between 1980 and 1983, droughts contributed only 17% in number but 41.3% ($144 billion) of the budget on mitigating disasters was taken up by droughts. In Europe, 5.3 billion Euros go into handling drought impacts annually.

Table 2-1: Impacts of natural disasters globally - 1900 – 2011

		Number of Events	Number of People Killed	People (Total) Affected	Damage (000 US$)
Africa	Drought/Drought	**275**	**844,143**	**330,651,357**	**5,419,593**
	Extreme temperature/Cold wave	5	73	1,000,105	47,000
	Extreme temperature/Heat wave	5	154	-	809
	Wildfire/Unspecified	1	49	3,023	-
	Wildfire/Bush/Brush fire	3	42	2,920	430,000
	Wildfire/Forest fire	9	66	11,140	-
	Wildfire/Scrub/grassland fire	13	117	14,532	10,000
Americas	Drought/Drought	**123**	**77**	**65,133,841**	**20,811,139**
	Extreme temperature/Cold wave	60	2,501	4,302,599	7,739,850
	Extreme temperature/Extreme winter conditions	7	82	910,047	-
	Extreme temperature/Heat wave	32	5,966	2,731	9,025,000
	Wildfire/Unspecified	4	1	56,823	2,016,000
	Wildfire/Forest fire	95	1,410	464,455	16,301,800
	Wildfire/Scrub/grassland fire	22	106	706,993	3,067,100
Asia	Drought/Drought	**149**	**9,663,389**	**1,668,036,029**	**31,739,865**
	Extreme temperature/Cold wave	65	7,752	5,737,757	1,389,627
	Extreme temperature/Extreme winter conditions	9	1,889	79,279,834	21,940,000
	Extreme temperature/Heat wave	55	11,000	23,801	401,000
	Wildfire/Forest fire	50	734	3,266,839	11,903,500
	Wildfire/Scrub/grassland fire	32	22	9,006	-
Europe	Drought/Drought	**38**	**1,200,002**	**15,482,969**	**21,461,309**
	Extreme temperature/Cold wave	89	4,086	770,345	2,291,700
	Extreme temperature/Extreme winter conditions	30	1,429	79,239	1,000,000
	Extreme temperature/Heat wave	59	133,637	2,120	12,763,050
	Wildfire/Unspecified	2	82	-	-
	Wildfire/Bush/Brush fire	1	53	5,996	1,800,000
	Wildfire/Forest fire	89	420	1,288,200	10,343,811
	Wildfire/Scrub/grassland fire	4	14	800	675,000
Oceania	Drought/Drought	**20**	**660**	**8,027,635**	**10,703,000**
	Extreme temperature/Heat wave	6	370	4,602,784	200,000
	Wildfire/Bush/Brush fire	1	180	9,954	1,300,000
	Wildfire/Forest fire	5	24	4,011	468,650
	Wildfire/Scrub/grassland fire	25	292	83,175	854,194

Created on: Nov-30-2011. - Data version: v12.07
Source: "EM-DAT: The OFDA/CRED International Disaster Database
www.em-dat.net - Université Catholique de Louvain - Brussels - Belgium"
Source: WHO Collaborating Centre for Research on the Epidemiology of Disasters (2012)

In all the continents, droughts have the greatest impacts in terms of number of people killed, affected and cost of damage (in US$). Below is further analysis of droughts.

Table 2-2: Impacts of droughts globally - 1900 – 2011

Continent	***Population (Appx.)***	***Continent's Contribution to the Droughts***		***People Affected***	
		Number	***Percentage of the total number***	***Total Number***	***%ge of the Population***
Africa	994,527,534	275	45%	330,651,357	33%
Americas	914,463,142	123	20%	65,133,841	7%
Asia	4,140,336,501	149	25%	1,668,036,029	40%
Europe	738,523,543	38	6%	15,482,969	2%
Oceania	36,102,071	20	3%	8,027,635	22%

With 45%, Africa contributed the highest percentage of droughts, which affected 33% of her population.

Drought is a topic 'loved' by researchers across all disciplines: hydrology, agronomy, ecology, geology, meteorology, computer science and environmental science. Droughts affect all corners of the globe irrespective of climatic zone and in terms of negative impacts, droughts are currently ranked[2] number one (CRED 2012).

Compared to other natural disasters such as floods, hurricanes, earthquakes and epidemics, droughts have very difficult to predict; they creep slowly and last longest. The complex nature of droughts onset-termination has made it acquire the title "*the creeping disaster*" (Mishra, Singh 2010). It may be difficult to determine when a drought begins or ends because of this creeping nature. It develops slowly and its impacts form a complex web that spans all aspects of life of the affected society. Hypothetically, drought prediction tools could be used to establish precise drought development patterns as early as possible and provide sufficient information to decision-makers to prepare for the droughts long before they happen. This way, the prediction can be used to mitigate effects of droughts. This is only possible if decision-makers both at the grassroots as well national/regional/international levels are availed with timely and accurate information about spatial and temporal dimensions of the droughts.

To accurately predict all the dimensions of a drought, one would be required to measure a battery of complex atmospheric and oceanic variables both local (to the location) and global.

[2] The ranking is based on severity, length of event, total area affected, total loss of life, total economic loss, social effect, long-term impacts, suddenness and frequency (Bryant 1991).

Examples of such variables are global atmospheric circulation, heat influx balance, land/sea proportions, heat capacities of the land and sea, the dependence of the reflectivity of the various areas and the complete set of local parameters. In the past, these variables were retrieved from historic climatic and meteorological data collected over a period of time at weather stations and also from reading satellite images. In our research, more variables were acquired from a database of traditional knowledge on droughts as well as readings from wireless sensors.

The timescales of drought can either be annual, monthly, weekly, daily, or hourly, depending on the variable being measured and the application of the prediction results. Despite the advancements in computer technology (for example, availability of powerful computers) and simulation algorithms/models, scientists are only able to provide indications of drought trends and never the actual values. Me-Bar, Veldez (2003) argue that droughts are random events (not deterministic) and compare them to ancient cultures where droughts were considered '*acts-of-gods'*. Models for predicting drought duration are more developed; however, those for predicting severity are still fraught with great difficulty and yet the latter is of paramount importance. Among other objectives, our research dwelt on measuring drought severity. Tadesse, Brown et al. (2005) propose the use of data mining as tool for drought analysis and prediction using satellite, climate and biophysical variables data.

2.1.4 Meteorological Drought Severity Indices

According to Panu, Sharma (2002), the severity of a drought is a function of the drought duration and probability distribution of the drought variable and its autocorrelation structure. Drought severity is in fact subjective; it has different connotations depending on the location/people as well as on the aspects of drought in consideration. In meteorological drought, the severity has rather been defined in the form of indices such as the Palmer Drought Severity Index (PDSI) (Palmer 1965). Agricultural droughts are analysed based on soil moisture modelling concepts with crop yield considerations and using multiple linear regression techniques. By getting to know the severity of drought, decision- makers can decide, for example, what water projects to initiate and also assist farmers to choose what crop to plant when and where. There are well-documented techniques and methods for analysing severity of meteorological and hydrological droughts (probability characterisation of low flows, time series methods, synthetic data generation, theory of runs, multiple regression, group theory, pattern recognition and neural network methods) but rarely for the agricultural droughts.

There are several well-developed indices for quantifying effects of droughts in terms of parameters such as intensity, duration, severity and spatial extent. These indices further map the droughts to different time-scales (daily, weekly, monthly, annually, and so on) and geographical regions to aid planning and decision-making processes. The best-known index for drought severity is PDSI; historically, it has been the most commonly implemented. Its weaknesses however range from its complexly to poor applicability (underlying computation is based on the climate of the Midwestern United States). This has led to various variations of the Index; such variations are: (1) the Standardized Precipitation Index (SPI) (McKee, Doesken et al. 1993), that measures the deviation of the actual precipitation from the average (reference) conditions in a given area; (2) Palmer Hydrological Drought Index (PHDI), which is used for water supply monitoring; (3) Self-Calibrated PDSI, which provided a solution to the inappropriately higher frequency of extreme drought (Wells et al, 2004); (4)Normalized Difference Vegetation Index (NDVI) on the other hand takes advantage of the reflective and absorptive characteristics of plants in the red and near-infrared portions of the electromagnetic spectrum; and (5) Available Water Resources Index (AWRI) that expresses the actual amount of available water (Wilhite, Glantz 1985).

Like the PDSI, SPI has it own share of popularity; however its major undoing (among others) is the predication granularity, which happens to be monthly scale. This way, it is not as accurate as required; it does not reflect daily/weekly patterns. Researchers such as Byun, Wilhite (1999) developed the Effective Drought Index (EDI) to address SPI shortcomings. EDI is different from the rest of the indices in a number of ways, one being that it calculates drought on a daily basis; the others use scales such as weekly, monthly bi-monthly, and so on. In this work, the interest is micro-level drought indicators and we therefore chose to use EDI. EDI was also chosen because it is the only one that quantifies droughts in absolute terms; one can tell exactly when the droughts start and end as well as the severity and the spatial distribution of the droughts. Some of the desirable features of EDI are: (1) It calculates daily drought severity; (2) It calculates more accurately the current level of available water resources; (3) It considers drought continuity, not just for a limited period; it can therefore diagnose prolonged droughts that continue for several years; (4) It is computed using precipitation alone and (5) It considers daily water accumulation with a weighting function for time passage. Calculation of EDI is made with consideration for the fact that the quantity of rainfall that can be used as a water resource drops gradually over time after the rain has fallen. Precipitations (EP) are used to compute deficiency or surplus of water resources for a particular date and place. EP here refers to the summed value of daily precipitation with a time-dependant reduction function; it makes use of equation 2-1 below.

Equation 2-1

$$EP_i = \sum_{n=1}^{i} \left[\frac{\sum_{m=1}^{n} P_m}{n} \right]$$

where P_m is the precipitation of m days before and the index i represents the duration of summation (DS) in days. Here i=365 is used, that is, summation for a year which is the most dominant precipitation cycle worldwide. The 365 can then be a representative value of the total water resources available or stored for a long time.

For instance, if i=2, then m varies from 1 to 2, EP_2 becomes [P1 + P1 + P2)/2]. Once the daily EP is computed, a series of indices can be calculated to highlight different characteristics of a station's water resources. These are: Mean Effective Precipitation (MEP), Deviation of EP (DEP) and Standardised Value of DEP (EDI).

In support of the need for EDI, Byun, Wilhite (1999), analysed the commonly used drought severity indices as shown in the table below:

Table 2-3: Characteristics of selected drought indices

Name	Factors Used	Time Scale	Main Concept
PDSI	*r, t,* et, sm, rf	m (2w)	Based on moisture input, output, and storage. Simplified soil moisture budget.
RAI	r	m, yr	Compare *r* to arbitrary values of +3 and -3, which are assigned to the mean of 10 extreme - and + anomalies of *r*.
Deciles	r	m	Dividing the distribution of the occurrences over a long-term *r* record into sections, each represents 10%.
CMI	r, t	w	Like the PDSI, except considering available moisture in top 5 ft of soil profile.
BMDI	r	m, yr	Percent departure of *r* from the long-term mean.
SWSI	P, sn	m	Weighted average of standardized anomalies of the main elements of the water budget.
SMDI	sm	yr	Summation of daily sm for a year.
CSDI	et	s	Summation of the calculated et divided into possible et during the growth of specific crops.
SPI	r	3m, 6m, 12m, 24m, 48m	Standardized anomaly for multiple timescales after mapping probability of exceedance from a skewed distribution.
RI	r	yr, c	Patterns and abnormalities of *r* on a continental scale.
RDI	*r, t,* sn, st, rs	m	Supply element–demand element.

KEY: P—factors used in PDSI, r—precipitation, et—evapotranspiration, t—temperature, sm—soil moisture, rf—runoff, sn—snowpack, st—stream flow, rs—reservoir storage, w—week, m—month, s—season, yr—year, c—century, 3 m—3 months. PDSI—Palmer Drought Severity Index; RAI —Rainfall; CMI —Crop Moisture Index Anomaly Index; BMDI — Bhalme and Mooly Drought Index; SWSI—Surface Water Supply Index; SMDI—Soil Moisture Drought Index; CSDI—Crop-Specific Drought Index; SPI—Standardized Precipitation Index; RI—National Rainfall Index; RDI—Reclamation Drought Index [Adopted from (Byun, Wilhite 1999)]

EDI has produced satisfactory results in measuring drought severity and was adopted (and adapted) to analyse 200-year drought climatology of Seoul, Korea (Kim, Hi-Ryong et al. 2009).

2.1.5 Drought Prediction and ICT - Where is the link?

The use of ICTs (both hardware and software) in weather monitoring comes with several advantages and may be utilised in all phases of the process; from parameters measurement, transmission, processing, storage to dissemination. For instance, Automatic Weather Stations are used in measuring and reporting a range of weather parameters with higher frequency. It is indisputable therefore that ICTs can be used to significantly improve drought prediction. The ITU (ITU-T 2008) acknowledged the critical role of ICTs, especially in addressing food insecurity (mostly a consequence of drought) and suggested that ICTs can be used: (1) to provide the remote sensing infrastructure, such as WSNs; (2) as the equipment (software and hardware) for analysis of drought data, including statistics, modelling and mapping, for example; laptops, servers, databases, GIS, data mining and neural networks; (3) as the communication infrastructure to disseminate the relevant information to farmers/consumers, for example Internet and mobile phones. The ICTs considered in ore research are:

Wireless Sensors

One of the ICT areas with highest potential is that of Wireless Sensor Networks (WSNs). The few implementations of WSNs for weather monitoring are found only in the developed world and rarely in the developing countries where much is needed to address the ever-increasing adverse effect of droughts on food security. A WSN is a collection of millimetre-scale, self-contained, micro-electro-mechanical devices that contain sensors, computational-processing ability, wireless receiver and transmitter technology and a power supply (Eiko, Bacon 2006). The now readily available, versatile and more cost-effective WSNs-based weather stations could be used to fill the lacuna left by the sparse network of relatively expensive conventional weather stations and enable self-sustainable operation in developing countries (Ziervogel, Opere 2010, Bagula, M. et al. 2012; Masinde, Bagula et al. 2012a). When deployed in their hundreds, they can enable capturing of weather parameters at micro-level and hence downscaling the forecast to a few metres as opposed to the current sparse networks of tens of thousands of kilometres.

Artificial Intelligent Techniques

The second contribution of ICTs to drought prediction is artificial intelligence techniques, especially Fuzzy Logic, Intelligent Agents and Artificial Neural Networks (ANNs). Agents have been known to perform well in conquering systems complexity as well in autonomous mission-critical systems. On the other hand, the ability of ANNs to use a ‘black-box’ approach to tackle very complex mathematical equations/formulas, like those found in drought prediction, has made them find applications in hundreds of hydrological/meteorological modelling applications. Fuzzy Logic, on the other hand, has the power to represent and manipulate information that has imprecise categorisation and generalisation, such as is the case with indigenous knowledge on weather.

Mobile Phones

Mobile phones are perhaps the most influential ICTs tool when it comes to drought prediction in SSA. One pointer to this fact is that although still experiencing a mobile phone penetration lag[3] of close to 10 years, Africa has achieved an average penetration level of 41% (ITU 2010b), which is much higher than that of computers. For instance, according to Kenya's 2009 population sensors (Kenya National Bureau of Statistics 2009) only 3.6% of households owned at least one computer in comparison with 63.2% of households that owned at least one mobile phone. With well-designed solutions, the use of these phones can be extended from the traditional use (as just communication devices) to computing devices on which weather forecasting applications can be executed. Examples of these are Grid and Service-Oriented Computing on mobile phones (Masinde, Bagula et al. 2010; Masinde, Zebal et al. 2012). In the context of this project, the phone plays not just the first/last-mile bit (capturing drought parameters and disseminating the drought alerts) but also a computing device.

2.2 Artificial Intelligence Techniques in Predicting Droughts

2.2.1 Overview

Artificial Intelligence (AI) refers to the computing paradigm that aims to develop solutions that mimic human perception, learning and reasoning to solve complex problems. Two AI techniques stand out when it comes to modelling environmental systems such as droughts; Intelligent Agents and Artificial Neural Networks. On the other hand, the holistic indigenous knowledge on drought forecasting can be modelled using Fuzzy Logic (Mackinson 2000; Krupnik and Ray, 2007; Lauler, Shankar 2008; Berkes, Mina 2009). Chen, Anthony et al. (2008) described and compared AI techniques' performance in modelling environmental system as summarised in Table 2-4 below. From these techniques, Fuzzy Logic, Agents and ANNs were applied in this research.

[3] The time gap between mobile phone penetration level in Africa, and the year that same level of penetration was achieved globally

Table 2-4: Characteristics of AI Techniques as applied in Environmental Modelling Applications

Technique	Description	Advantages	Disadvantages
Case-Based Reasoning (CBR)	Solves a problem by recalling similar past problems with similar solutions (Aamodt 1994); it applies four steps: retrieve, use, revise and retain.	It supports continuous improvement in reasoning capability and accuracy and by extension, performance.	Though not for complex systems, CBR is based on 'black-box' approach black that offers minimal insight into the system and processes involved.
Rule-Based Systems (RBS)	Uses an expert knowledge to derive rules and applies them in solving problems. The rules follow the '*if-then'* syntax to reach decisions.	They are easy to understand, implement and maintain.	Not suitable for ecological systems because they have complex interactions and processes often not well understood.
Artificial Neural Networks (ANNS)	These are highly interconnected systems that operate by mimicking the operation of the human brain. ANNs perform seven categories of tasks: pattern classification, clustering, function approximation, prediction, optimisation, retrieval by content and process control.	Excellent in solving data-intensive and multivariable problems with unclear mapping rules.	Also based on 'black-box' concept and therefore not good for problems that need explanation of the process used to solve them.
Genetic Algorithms (GA)	Mimics the rule of natural selection and solves problems by iterating until a satisfactory solution is found.	They have simple and robust, computation approach with efficient load balance. They support high level of implicit parallelism.	It takes large computation time and sometimes premature convergence on a local optimum may occur.
Cellular Automata (CA)	Made up of dynamic models, discrete in space, time and state. They consist of regular lattice of cells which interact with their neighbours. CA supports four types of patterns (I-IV); homogeneous, simple separated periodic structures, chaotic aperiodic patterns or a complex pattern of local structures.	They are made up of simple mathematical models that can simulate complex physical systems. They can incorporate interactions and spatial variations, and also spatial expansion with time.	The main problems emanate from the reflection and absorption boundary conditions. Boundary conditions are also unlikely to reflect real life and have limited capacity to make precise predictions.
Fuzzy Systems (FS)	They make use of fuzzy sets to deal with imprecise and incomplete data. Data sets here have values between 0 and 1 and therefore can be used to describe vague statements as in natural language. FS apply techniques such as maximum, mean-of-maxima and centroid defuzzification.	The strength comes from the ability to handle imprecise and incomplete information similar to what human being have to deal with. They are also easier to understand and apply.	They have no learning capability or memory.
Multi-Agent Systems (MAS)	An agent is an autonomous piece of software component containing code and data; MAS is network of agents interacting to achieve goals. Suitable for problems needing fast, concurrent processing to arrive at a solution without conflict resolution.	Their ability to represent complex systems with several stakeholders and allow exploration of alternative management approaches.	They are however, more suited to social learning among interest groups than prediction of system behaviour.
Swarm Intelligence (SI)	It is a form of agent-based modelling inspired by colonies of social animals such as ants and bees; they utilise the 'more are better than one' policy. Two commonly used algorithms are Particle Swarm Optimisation (PSO) and Ant Colony Optimisation (ACO),	SI strength is its two algorithms; they are versatile yet simple enough to be readily accessible for practical applications and easy to implement. The ability to mask out failures and self-organisations gives SI the ability to solve dynamic problems.	They are less efficient in performing non-linear optimisation with a population of potential solutions.
Reinforcem ent learning RL)	Involves learning through interaction between a learning agent and its environment; the agent learns to achieve a goal by trial and error. Three types of RL pure delayed reward, minimum time to goal and games	Useful when there is need to creates new behaviour rather than modelling existing behaviour.	Limited studies have applied RL alone to solve environmental problems. On its own, It is difficult to formulate a policy that works successfully in real life.

2.2.2 Artificial Neural Networks

For decades, pattern reorganisation techniques, regression models and autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) models for statistical time series have been used for drought forecasting. ANNs provide one of the nonlinear non-stationary alternative models for drought forecasting and as stipulated by Mishra, Desai (2006). ANNs have several advantages to this end; they can be used to solve problems with nonlinear/unknown multivariate and less controlled environments (Bodri, Cermak 2001). The greatest strength of ANNs, though, is its ability to weave together various mathematical components capable of tackling very complex physical systems such as droughts. ANNs are also flexible and less assumption-dependent and this has seen them find applications in modelling extremely complex domains such as rainfall-runoff, stream flows, water quality and precipitation estimation (ASCE Task Committee on Application of Artificial Neural Networks in Hydrology 2000). In most hydrological applications, multi-layer perceptron (MLP) neural network model is adopted with feed-forward back propagation (BPN) as the training algorithm (Freitas, Billib 1997; Antonić, Josip et al. 2001; Bodri, Cermak 2001; Kung, Hua et al. 2006; Mishra, Desai 2006; Chang-Shian, Boris et al. 2010). Antonić, Josip et al. (2001) used seven climatic variables obtained from 127 weather stations in Croatia to develop empirical drought models using BPN. Mishra, Desai (2006) observed that most ANNs' implementations adopted the multi-layer feed-forward neural network and were based on BPN.

BPN has been applied in modelling animal/plant population growth to predict hydrological/meteorological phenomena such as droughts and floods. BPN has three general layers: input, hidden and output, and has two processing types: learning/training and recalling. At the input layer(s) data are fed to the system while the processing takes place within the hidden layer(s) and finally, results are produced at the output layer(s) (Morid, Vladimir et al. 2007). Besides it being difficult to determine the representativeness of learning data, using BPN in hydraulic modelling is faced with the problem that BPN is a non-linear black box that does not consider/explain the underlying physical process of watershed (Chang-Shian, Boris et al. 2010; Chang-Shian, Boris et al. 2010). This is the weakness that Chang-Shian, Boris et al. (2010) tried to address using Decision Group BPN. Using a data (precipitation) set for 36 years (1965 to 2001), Mishra, Desai (2006) compared the performance of BPN and ARIMA for different Standard Precipitation Index (SPI) series. Applying both the Recursive Multi-step Neural Network (RMSNN) and the Direct Multi-step Neural Network (DMSNN) approaches, they found that RMSNN performed better than both DMSNN and ARIMA for one-month lead-time and that DMSNN performed better than the other two for a lead-time of four months. Other projects in which ANNs have been used for predicting droughts/floods include drought prediction in north-east Brazil (Freitas, Billib 1997), summer flood forecasting in Moravia (Bodri, Cermak 2001). Shin, Salas (2000) used ANNs to quantify the spatial and temporal patterns of meteorological droughts for the south-western region of Colorado.

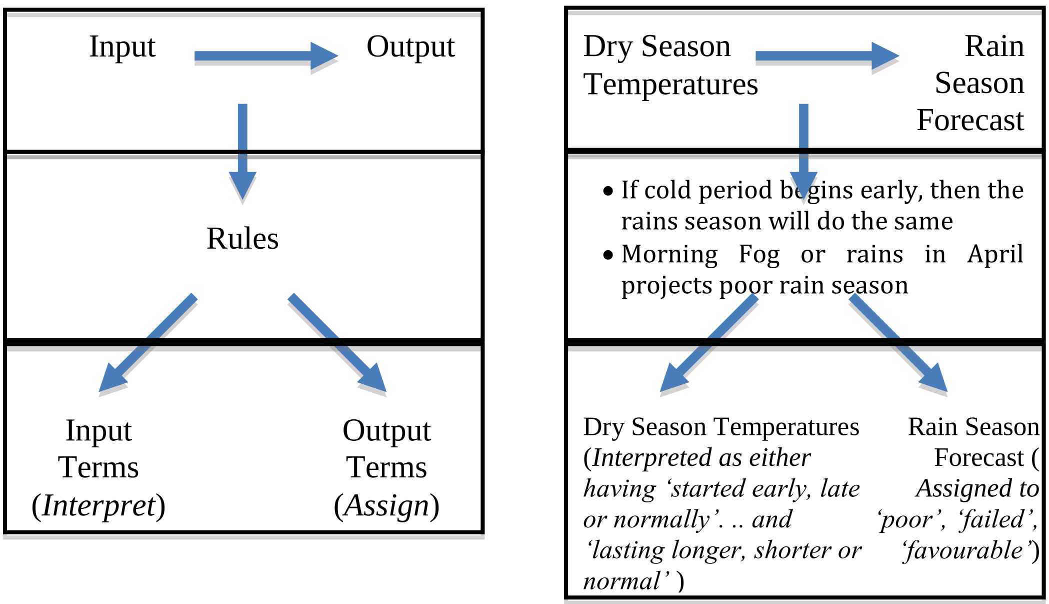
In the work titled "*Drought forecast model and framework using wireless sensor networks*", by Kung, Hua et al. (2006), a four-tier Drought Forecast and Alert System (DFAS) is described. The system consists of: (1) wireless sensors to collect ecological real-time spatial drought inference factors such as soil and air moisture and air temperature; (2) mobile computing devices to allow users access drought information in a variety of formats; (3) multiple intelligent agents' implementation for data collection, searching, classifying, processing and notifying about droughts; (4) drought detection module that uses the real-time data from the sensors and non-real-time data on 30-days' mean rainfall from weather stations and satellite images from Moderate Resolution Imaging Spectroradiometer (MODIS) to come up with drought levels. The drought level of the 7th day is computed using the Back Propagation Network algorithm within Artificial Neural Networks. The rationale for 7th day was based on the argument that shorter timescales did not make operational sense and that higher timescales would lead to inaccurate results owing to changing climate. Five drought classification levels applied in this project are: '*non-drought*', '*slight drought*', '*moderate drought*', '*serious drought*' and '*extreme drought'*. These were used as the output values for training the Back Propagation Network. Given that all the input factors into their drought prediction model, Kung, Hua et al. (2006) were able to forecast both meteorological and agricultural droughts. The system was implemented in Neipu, Taiwan using MIB510, MPR400, MDA300 and MTS420 sensor motes as well as Compaq Pads and networked cameras.

Apart from being so specific to the Nuepu, Taiwan, implementing DFAS in SSA would be an unaffordable project. Two, both positive (floods) and negative (droughts) must be factored into any complete drought prediction system; DFAS only takes care of negative values. The third limitation of DFAS is the fact that the most crucial input (rainfall) to a drought prediction algorithm is retrieved from weather stations; there are no adequate weather stations in most SSA countries to provide credible data. A drought prediction solution for SSA must address the current weather stations' sparse network.

2.2.3 Fuzzy Logic

Basic Concepts

Fuzzy logic was conceptualised by Zadeh (1965, 1973) and is defined in Mathworks (2005) as a convenient way to map an input space to an output space. The duo also explained several advantages of using fuzzy logic; the most relevant to this research work being the fact that it can model imprecise data and nonlinear functions of arbitrary complexity and that it is based on natural language. Fuzzy logic applications range from soil science, (McBrateney, Odeh, et al. 1997; Sicat, Emmanuel, John, Carranza et al. 2005; Giordanoa, et al. 2011) to Geographical Information Systems (Robinson 2003). The general concept behind fuzzy logic is that a set of pre-defined rules (if-else-statements) are applied in parallel to interpret some values in the input vector and then assign values to the output vector. The figure below (adopted from Mathworks, 2005) explains this concept.



(a) General Case (b) IK Weather Forecasting Example

Figure 2-1: Fuzzy Logic Concepts

(adopted from: **Mathworks (2005)** .

In classical sets, (Boolean or crisp) set theory, membership of an element *x* in a set ***A***, is defined by a characteristic function which assigns a value of either 1 (true) or 0 (false) to each individual in the universal set X. That it is to say; "*every proposition is either true or false*". For example, the Effective Drought Index drought classes (Byun, Wilhite 1999) may be defined as follows:

- Extreme drought - EDI $\leq$-2.0
- Severe drought - -2.0 < EDI $\leq$-1.5
- Moderate drought - -1.5< EDI $\leq$-1.0

From this, a characteristic function for 'Severe Drought' implies that EDI values of -.2.00 and -1.49 are not in the 'Severe Droughts' set and yet values -1.99 and -1.50 are in this set. In real sense, all these values actually represent severe droughts at differing degrees weights. This is where Fuzzy Logic comes in; it allows membership in more than one set; -2.00 can be in the 'Extreme Drought' and 'Severe Drought' sets while -1.49 can be in both 'Severe Drought' and 'Moderate Drought' sets at varying degrees. Fuzzy Logic therefore violates both 'excluded middle' and 'contradiction' laws (Klir, Bo 1995).

Fuzzy Logic is based on fuzzy sets in that, unlike classical sets, their membership is not a '*true-false*' but '*not-quite-true-or-false*' answer. For example, a rainy season forecast's membership in the set 'favourable-season' is not a true-false mapping but, rather it has continuous range of values ranging between 'false' and 'true'.

A fuzzy set A is made up of ordered pairs and is defined as follows:

$A=\{x| \mu_A x) | x \in X\}$

where ***X*** is the universe of discourse whose elements are denoted by ***x***. and ***μA(x)*** is the Fuzzy Membership Function of ***x*** in ***A***. This is a value in the unit interval [0,1], where 0 means that an attribute has complete non-membership in a fuzzy set; 1 means that an attribute has complete membership in a fuzzy set, and grades between 0 and 1 mean partial membership in a fuzzy set.

This value (grade) is associated with a certain proposition in the domain being modelled. For example, "*based on the strength of the indigenous knowledge weather indicators observed between November and May, the rain season (June to October) is going to a favourable one*".

Fuzzy Membership Function

A Fuzzy Membership Function (FMF) is a curve that defines how each point in the input space (*universe of discourse*) is mapped to a membership value (or degree/grade of membership) between 0 and 1. In the current work, the input space for weather forecasts for a given community refers to all indicators (meteorological, animal behaviours, etc.) used to forecast weather. The choice of a FMF to be used is determined by the domain of the application as well as its simplicity, convenience, speed, and efficiency (Mathworks 2005). FMFs are often defined in terms of standard basic functions such as piecewise linear functions, the Gaussian distribution function, the sigmoid curve, and quadratic and cubic polynomial curves. The latter are categorised as either open (decreasing and with values between 0 and 1 only within a bounded interval) or closed category that allows non-zero values only in a bounded interval (Robinson 2003). The two main classes under the open category are linear (usually left or right trapezoid function) and S-shape (left or right open shoulder) membership functions. Examples of functions under the closed category are: triangular (in general, the most commonly used category), trapezoidal, sigmoidal and generalised bell functions.

Gaussian and sigmoidal are two S-Shaped membership mirror-image functions that open to the right and are based on polynomial curves. They are suitable for modelling indigenous knowledge because they have been proven to be appropriate and robust for linguistic variables (Sicat, Emmanuel, John, Carranza et al. 2005). Both of these curves have the advantage of being smooth and nonzero at all points and are (among others) supported within the MATLAB Fuzzy Logic Toolbox that was used in modelling IK data in this work.

Logical Operations

Given that in Fuzzy Logic, the truth of any statement is a matter of degree, the standard logical operations have been modified to work for in Fuzzy Logic as follows:

- Fuzzy intersection or conjunction; A AND B → min(A,B)
- Fuzzy union or disjunction; A OR B → max(A,B)
- Fuzzy complement (NOT A) → 1-A

The operations above retain the values of the standard logical operations truth table.

IF-THEN rules are used in Fuzzy Logic to construct complete sentences; they have the format:

IF *x* is A THEN *y* is B; where A and B are linguistic values defined by fuzzy sets on the ranges (universes of discourse) X and Y, respectively.

The IF-part of the rule “x is A” is called the ***antecedent*** or ***premise***, while the THEN-part of the rule “y is B” is called the **consequent** or ***conclusion***.

Example: *IF mango trees under type-1 produce abundance fruits, THEN the millet will do the well in Mbeere.*

Fuzzy Modelling Stages

There are three stages of fuzzy modelling (Mathworks 2005; Sicat, Emmanuel, John, Carranza et al. 2005):

i. **Fuzzification** of the inputs; generation of FMFs for input to a degree of membership between 0 and 1
ii. **Logical Inference** procedures – that is fuzzy set operations that combine fuzzy sets into a synthesised fuzzy set. This entails resolving the antecedent the IF x) part(s) to a single number between 0 and 1
iii. **Defuzzyfication** – transformation of synthesised fuzzy set back to a crisp sets. It involves assigning an entire fuzzy set to the output based on the consequence of a fuzzy rule.

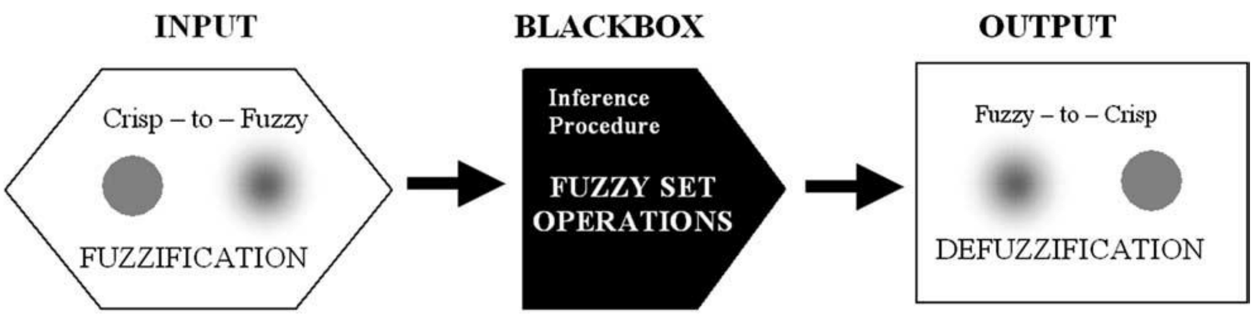


Figure 2-2: Main stages in fuzzy modelling

(*Adopted from Sicat, Emmanuel, John, Carranza et al. 2005)*

In real-life, multiple fuzzy rules are used; output of each rule is a fuzzy set. All these sets are aggregated into a single output fuzzy set which is then **defuzzified** into a single number. This mapping (input to output) process is called ***fuzzy inference*** (Mathworks 2005).

MATLAB Fuzzy Logic Toolkit

In the MATLAB Fuzzy Logic Toolkit that was used to model IK, above fuzzy logic steps are carried out in the following five steps:

Step 1: Fuzzify Inputs – for each of the inputs, the degree to which they belong to each of the appropriate fuzzy sets (via membership functions) is determined, for example a OND rain season started late, early or normally or a given type of mango trees' production was poor or good, and so on.

Step 2: Apply Fuzzy Operator – these are used when the antecedent part of a rule has more than one part: fuzzy operators (AND-min, OR-max, etc.) are applied to resolve it into a single rule. For example, "*if the MAM rain season onset is delayed AND it is accompanied by empty thunderstorms THEN the season will be poor*"

Step 3: Apply Implication Method – this is the shaping of the consequent (a fuzzy set) based on the antecedent (a single number). This is determined by the rule's weight (relative to other rules in the rule set). This could be done using min (minimum), which truncates the output fuzzy set, and prod (product), which scales the output fuzzy set.

Step 4: Aggregate All Outputs –unify the outputs of each rule by joining the parallel threads. This is achieved via three in-built methods; max (maximum), probor[4] (probabilistic or), and sum (simply the sum of each rule's output set).

Step 5: Defuzzify – that ensures that the final output for each variable is a single crisp number. This is achieved by applying any of the following five in-built methods supported: centroid, bisector, middle of maximum (the average of the maximum value of the output set), largest of maximum, and smallest of the maximum.

Example

Fuzzify Input:

- If (ONDSeasonCharacteristics is 'StartsLate') or (DryHotSeasonCharacteristics is NOT VeryHighTemperatures) or (LeavesFlowersFruitsProduction is HighPropductionByTypeA)
- If (ONDSeasonCharacteristics is AccompaniedByHails) or (DryColdSeasonCharacteristics is StartsEarlyEndsEarly) or (DryHotSeasonCharacteristics is Longer) or (LeavesFlowersFruitsProduction is NOT HighPropductionByTypeA)

[4] The probabilistic OR method (also known as the algebraic sum) is calculated according to the equation: *probo* $((a,b) = a + b - ab$

Apply Fuzzy Operator:

- then (AnticipatedHarvest is PoorHarvest)
- then (AnticipatedHarvest is GoodHarvest)

Supposing ‘Poor Harvest’ is a fuzzy set whose values range from 0.2 to 0.4, and those for the fuzzy set ‘Good Harvest’ are from 0.7 to 0.9 then

Apply Implication Method:

min(PoorHarvest) = 0.2

min(GoodHarvest)=0.7

2.2.4 Belief-Desire-Intension Agents

Agents have been known to perform well in conquering systems complexity as well as in autonomous mission-critical systems. The characteristics of an agent include: well-defined problem boundaries and interfaces; is embedded in a particular environment; is designed to achieve specific objectives; is autonomous and is flexible and display (context-dependent) problem-solving behaviour - it is reactive. Agents have the following basic structure (Schalkoff 2011):

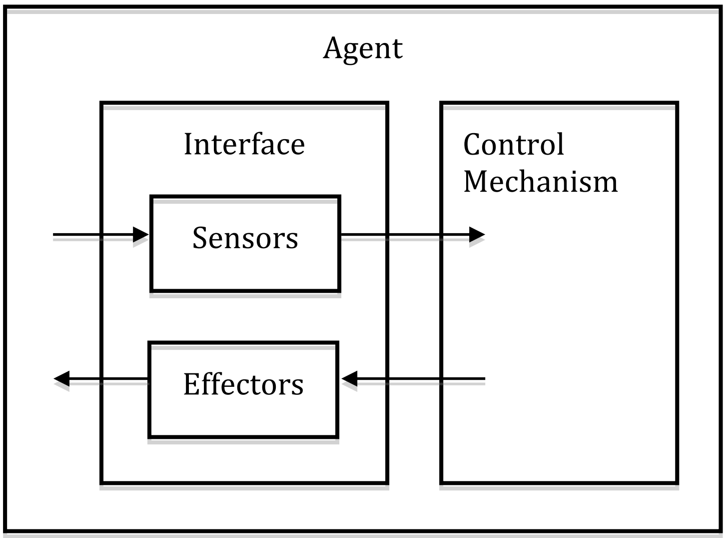


Figure 2-3: General Structure of an Agent

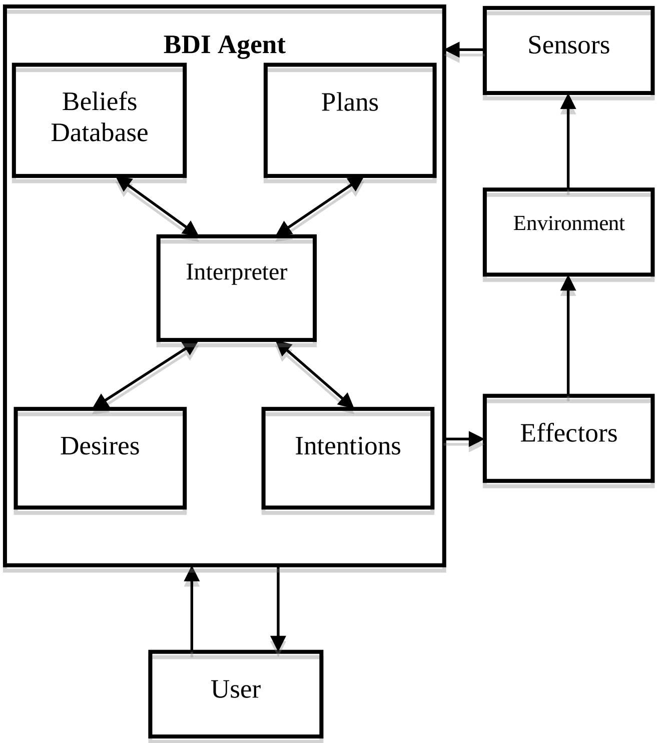
The greatest strength of agents is the ability to be autonomous; this is supported by the following agents’ capabilities (O’Hare, G., M., P., Jennings, N., R. 1996): (1) Perception and interpretation of incoming messages and data; (2) Reasoning upon their beliefs; (3) Decision-making (goal selection, solving goal interactions, reasoning on intentions); (4) Planning - selection or construction of action plans, conflict resolution and resource allocation; (5) Ability to execute plans including message-passing. Agents are classified based on various degrees of problem-solving capabilities.

Two main categories of Agents are: *Reactive Agents* that are able to react to changes in the environment or messages from other agents and *Intentional Agents* which are able to reason on their intentions and beliefs and to create plans and actions and execute those plans.

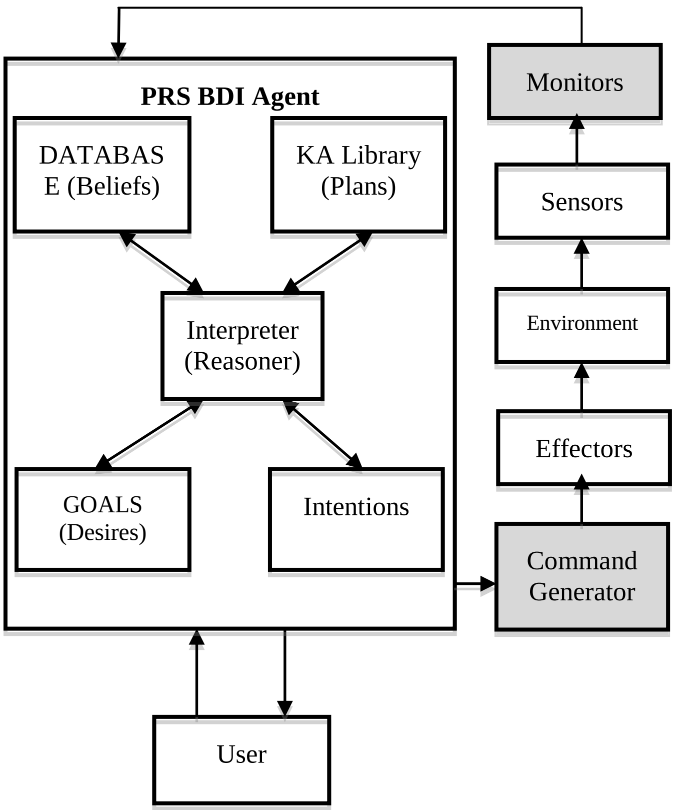
Belief Desire Intension (BDI) Agents is a category of agents that was established in the 1980s. BDI resulted from studies aimed at comparing agents to the psychological studies of human related to motivations such as desires, goals and preference. This referred to systems whose behaviour can be described by attributing to the system mental attitudes such as '*belief*', '*preference'* and '*intention'*. These attitudes are further classified into: *Cognitive* – epistemic issues such as belief and knowledge; *Conative* – issues related to action and control such as intention, commitment and plan; and *Affective* – issues. From these, *Belief, Desire* and *Intention* were used to represent each of these categories and hence the name BDI Agents. *Belief* is used to represent what the agent holds about the environment and about itself; this is in no way related to the beliefs as defined in the indigenous knowledge domain. On the other hand, *Desire* and *Intention* represent the state of affairs that the agent wishes to bring out. Intentions differ from desires in that Intentions is the measure of commitment that leads and controls the future actions of the agent; an agent may have desires but never set out to fulfil them (JACK 2011).

The main components of BDI are: a database of beliefs consisting of world facts as well as data relevant to the agent's internal state; a set of the agent's goals or objectives (desires); a set of plans necessary to achieve these goals; and an ordered set of these plans (intentions).

Various BDI architectures have evolved over time; two of these are: Intelligent Resource-bound Machine Architecture (IRMA) and the Procedural Reasoning System (PRS). PRS was created as a BDI architecture that could be used in real-world applications, and was aimed at supporting both goal-directed and reactive reasoning. It was first used in the implementation of a task control system for a NASA spacecraft simulator. It has four components (Schalkoff 2011): a database containing the current system's beliefs about the world; a set of current goals; a procedure or plan library knowledge area (KA) library); and an intention structure.



(a) Basic Structure



(b) PRS Structure

Figure 2-4: PRS BDI Structure

In terms of practical reasoning, BDI is the best-known agents' model whose strength stems from its ability to implement philosophical model of human practical reasoning (Georgeff, Barney et al. 1998); it has been successfully applied in several applications. Of all the Agents programming environments (such as LEAP, JACK, ZEUS, etc.), BDI is implemented in JACK and Agents Factory (AF). Besides being open-source, a comparison of these two by Rem, Gregory et al. (2003) further reveals that AF supports more features than JACK. On the other hand, JACK is a commercial product with well-orchestrated user support (JACK 2011). The greatest strength of JACK is its flexibility and extensibility, which is due to the fact that all components are implemented as Java plug-ins. BDI model is also implemented in Jadex (Pokahr, Lars et al. 2003) and SPARK Agent Framework (Morley, Myers 2004).

As mentioned earlier, drought prediction is a complex which BDI model of agency could address. Systems that have some aspects similar to the one described in this research are such as the one described in Javier, Juan (2005) where a combination of BDI and Case-Based-Reasoning (CBR) was used to develop a model that calculates the global air-sea flux of CO^2 exchanged between the atmosphere and the surface waters of the ocean, as well as the global budgets of CO^2 for the whole oceanographic basin. In Mehdi, Ghorbani (2004) a network intrusion monitoring and detection was developed using JACK.

2.3 Indigenous Knowledge Weather Forecasts

2.3.1 Definitions

Indigenous knowledge, also referred to as 'local knowledge', 'traditional knowledge', 'indigenous technical knowledge', 'peasants' knowledge', 'traditional environmental knowledge' and 'folk knowledge' (Sillitoe 1998) is a body of knowledge existing within or acquired by local people over a period of time through accumulation of experiences, society-nature relationships, community practices and institutions, and by passing it down through generations (Brokensha, Warren. et al. 1982;, Fernando, Jayawardena et al. 1998; Sillitoe 1998; Orlove, Roncoli et al. 2009). In Steiner (2008) indigenous/traditional knowledge (IK) is described as the knowledge of an indigenous community accumulated over generations of living in a particular environment. It is traditional cultural knowledge that includes intellectual, technological, ecological, and medical knowledge. In IK forecasting, the local weather and climate are assessed, interpreted and predicted by locally observed variables and experiences using combinations of plant, animals, insects and meteorological and astronomical indications (Boef, Kojo et al. 1993).

In Orlove, Roncoli et al. (2009), the term indigenous knowledge is used to refer to the 'place-based knowledge' that is rooted in local cultures and generally associated with long-settled communities, which have strong ties to their natural environments. In some quarters, the term "indigenous knowledge" is in fact, unwelcome. For example, in Roncoli (2002), the term is said to connote colonising discourse and policies in much of francophone Africa. Indigenous Technical Knowledge (ITK) or Traditional Environmental Knowledge (TEK) tends to reify diverse and fluid cognitive dimensions into an inflexible package of disembodied know-how. Farmers Knowledge (FK) or Local Knowledge (LK) evokes the performance element of knowledge and the contextual aspect of its practice (Richards 1993). The common convergence of these terms is that this 'knowledge' encompasses shared selective repertoires and has two main aspects: (1) natural phenomena and (2) cultural and ritual spiritualists derived through divination, visions and dreams. All these definitions are in agreement that IK is based on cumulative experience and observation of the environment and normally developed through oral communication and repetitive engagement rather than through formal instruction.

2.3.2 Precepts of Indigenous Knowledge on drought forecasting

The entry point for the forecasting is the amassed knowledge of exact arrival of the rainy season. The local community has built this knowledge over the years from their understanding of the forecasting and the probability of future rain based on variance in wind, humidity and temperature. Secondly, based on the kind of social-economic activities the community indulges in, interpretations of animals, insects, birds, and plants behaviour is performed. These generally affirm the rainy season indicators because the plants/creatures observed exhibit subtle fluctuations in temperature and humidity. This category of indicators is generally used to forecast short-term (hours or days) trends. Finally, IK forecasting is based on observing historical trends; this is one of the precepts whose reliability is currently under threat due to the increased severity and frequency of droughts over the last decades across the entire world (Mutua 2011). IK on drought forecasting in the tropics falls into six general categories: (1) patterns of seasons (cold, dry, hot, rainy and so on); (2) animal, insects and bird's behaviour; (3) astronomical; (4) meteorological; (5) human nature and behaviour; and (6) behaviour of plants/trees, for example fruit and flower production.

Communities have informal ranking systems based on factors such as the source (who reported the indicator) and coverage (how widespread it is). For example, among some pastoralist communities living in Northern Kenya and South of Ethiopia (Luseno, McPeak et al. 2003), the following ranking is used:

(1)Intestine (2) Clouds (3) Birds (4) Livestock behaviour (5) Stars (6) Trees (7) Wind (8) Night Sky (9) Moon (10) Shoes (11) Plants (12) Dreams (13) Year type (14) See lightening (15) Frogs (16) Butterfly (17) Climate (189) Month

The indicators are used in a holistic approach; some indicators need to be authenticated by other 'stronger' indicators. Further, some indicators may have more than one interpretation and others are composite; more than one indicator is needed to reach one particular decision.

2.3.3 Indigenous Knowledge on Droughts

Since time immemorial, from Australia to Asia, Africa to Latin America, local communities have continued to rely on their own indigenous knowledge systems in dealing with disasters triggered by climatic variations such as droughts and floods. This is especially so for communities living in disaster-prone areas; they have vast bodies of knowledge on disaster management and mitigation strategies, early warning preparedness and recovery. This is based on cumulative experiences passed down generation after generation (Stigter, Baldy 1995; Aparna, Trivedi 2011). Today, with more frequent and severe climate variability incidents, the use of indigenous knowledge methods and technologies are being revived especially for managing Low External Inputs Sustainable Agriculture (LEISA) (Stigter, Baldy 1995). There is literature-supported evidence that indigenous knowledge leads to success stories. In 2002, torrential rains experienced in Mbeere swept away a modern bridge but left the traditional bridge (***itiki***) intact (source: first-hand witness by the author). Phillips, Deane et al. (2002) reported that in both 1997/98 and 1998/99, Zimbabwean farmers' seasonal climate forecasts, elicited in advance of the release of official climate forecasts, corresponded almost exactly with the official meteorological service forecasts.

Some aspects of indigenous knowledge are based on beliefs and on cultural and ritual spiritualists who predict rainfall from divination, visions, and dreams. Other aspects are derived from historical experiences, for example, in Rakai District of Uganda, the farmers' believe that if one season is unfavourable because of its scanty or irregular rains or of its short duration, then the next season will be better (Orlove, Roncoli et al. 2009). A survey carried among the Mbeere people came across a belief similar to the latter (Masinde, Bagula et al. 2012b). As such, some of these characteristics of indigenous knowledge on droughts are fit to be classified under '*tacit knowledge'*. In the latter, "*people often arrive at the correct answer, sometimes by inappropriate, imprecise or even incorrect means because they know and can implement knowledge and skills that cannot be readily explained"* (Polanyi 1966). All in all, this suite of traditional methods seems to offer sufficient complementary knowledge as to elicit confidence. Examples of indigenous knowledge on weather/climate include: observing clouds and stars/sun/moon; watching the behaviour of livestock, wildlife or local flora; reading the intestines of slaughtered animals and interpreting dreams or the patterns in which pairs of shoes fall when repeatedly thrown (Luseno, McPeak et al. 2003; Roncoli 2006; Mugabe, Mubaya, Nanja et al. 2010). Despite this categorisation, interpretation of IK is based on extremely site-specific patterns (Hammer, Hansen et al. 2001).

2.3.4 Indigenous Drought Forecasts in African Communities

Traditionally, small-scale farmers in Africa have always based their major decisions on Indigenous Knowledge of weather and climate patterns (IKFs). Some of this knowledge is, however, so intertwined with the communities' cultural and religious beliefs that it is very difficult to put it into conventional reasoning based on modern science. Though this is changing, the nature of this indigenous knowledge has made the modern scientists brand it as '*primitive'* and inferior to scientific knowledge (Roncoli 2006). Generally, publications on IK of drought/weather management in Africa (Ziervogel, Opere 2010; Downing, Washington 1997; Ajibade, Shokemi et al., 2003; Luseno, McPeak et al. 2003; Roncoli 2006; ISDR 2006; Steiner 2008;, Orlove, Roncoli et al. 2009; Mercer, Kelman et al. 2010; Roos, Shingairai et al.

2010; UNEP 2011; Ziervogel, Opere 2010) reveal that communities in Africa used common approaches in predicting drought/weather. They observed changing seasons as well as lunar cycles (shape/position of the moon and patterns of stars). They also observed the natural environment (behaviour of animals/birds and looks of some plants) and like the weathermen of today, they studied the meteorological parameters such as air/temperature intensity, clouds colour/direction and wind direction. Religious beliefs and myths also contributed greatly to African indigenous knowledge on droughts prediction. For example, rainfall is seen as gift from the gods and lack of it as a curse. For example, in reference to the May 2011 drought that affected some parts of Mbeere in Kenya, residents were often heard saying; "*We do not know what God wants with us!" (*Masinde, Bagula et al. 2012). Other examples are: (1) mating of animals was a sign that there was going to be plenty of rains (Roos, Shingairai et al. 2010; Masinde, Bagula et al. 2012b); (2) wind blowing to the west would bring rainfall in an hour (Ajibade, Shokemi et al., 2003, Masinde, Bagula et al. 2012b).

Indigenous knowledge on droughts in Africa is a twin reality: predictions as well as spelling out elaborate coping mechanisms. When drought strikes the Mbeere people, the women specialise in weaving baskets using (mostly) locally available materials and then travel to Central Kenya (Kikuyu land) to exchange them for cereals(Masinde, Bagula et al. 2012b). Similarly, the women among Batswanas of South Africa engage in creative activities such as making clay pots for water storage as well for entrepreneurial purposes (Shingairai et al. 2010). Herders employ elaborate livestock management strategies based on regular, opportunistic migration in search of sufficient forage and water, herd splitting, rapid destocking, complex gift and loan systems, and raiding other clans' and ethnic groups' herds (Luseno, McPeak et al. 2003). Far away from Africa, indigenous residents of Tikopia Island in the Solomon Islands struck by Cyclone Zoe in December 2002 survived using age-old indigenous practices of traditional housing, some of which survived the cyclone (Mercer, Kelman et al. 2010). African communities also have common food preservation practices such as meat drying and stockpiling; these are meant to ensure food availability during shortages. This nature of indigenous knowledge on weather spans beyond Africa: similar characteristics were noted regarding the indigenous knowledge on weather for the Rajasthan area in India (Aparna, Trivedi 2011).

2.4 Seasonal Climate Forecasts

2.4.1 Overview

The main climate variables of interest for societal applications are atmospheric temperature, rainfall and humidity (Jury 2008). Seasonal Climate Forecasts (SCFs) need to be tailored to feed application models such as crop models, disease models and hydrological models, or to feed user-specific decision processes. The current approaches used for producing seasonal climate forecasts include the use of: (1) physically based dynamical global/general climate models GCMs) made up of codified equations representing the physical processes of the atmosphere. It involves analysis of interaction between the different dynamic components of ocean, land, and atmosphere to produce medium-course (~300km) forecasts (Lau, Young et al. 1999; Saha, Nadiga et al. 2006; Anderson, Stockdale et al. 2007; Doblas-Reyes, Weisheimer et al. 2009); (2) regional climate models (RCMs), also known as limited-area GCMs carries out the same tasks as GCMs but at a limited domain. The forecast here is higher resolution (~75km) and includes local small-scale physical phenomena and local knowledge of the topology/vegetation (Barron, Sorooshian 1997; Lau, Young et al. 1999); (3) empirically based statistical: based on statistical models built using past observations model(s); and (4) a combination of dynamical and empirical models

These models generally produce forecast information at coarse spatial resolution (of the order of 100–200 km, which is presented as the probability of the seasonal rainfall being in the '*above normal*', '*below normal*', or '*normal*' compared with historical trends. This may have contributed to the current status where the utilisation of such forecasts in SSA is still dismal. In West Africa, for example, efforts to disseminate and apply forecasts are at an experimental stage (Roncoli 2002). As application models usually require climate forecast information at much refined spatial and time resolution (Ghile, Schulze 2008), there is need for downscaling the forecasts produced by climate models to the desirable level of details required in real-life application models (Hansen 2002). The first step is to derive the seasonal forecasts (Washington, Downing 1999); this is often achieved through the following stages:

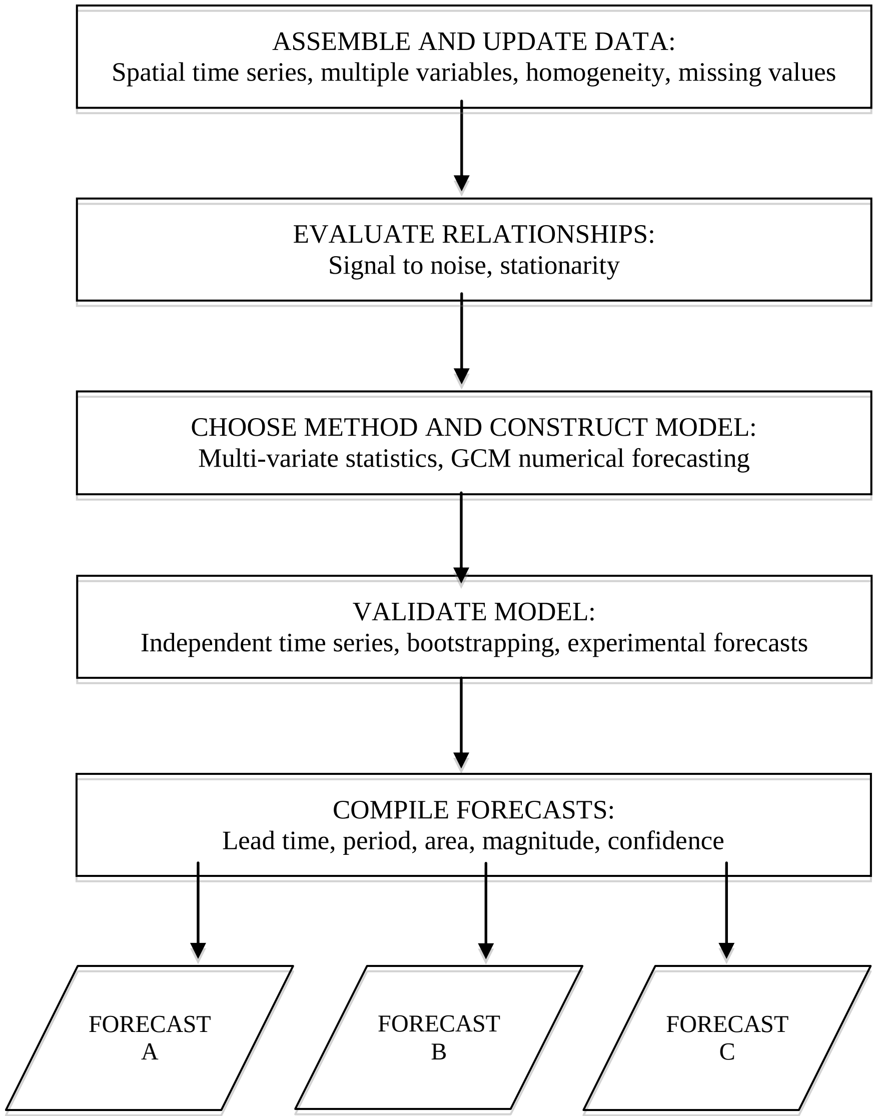


Figure 2-5: Stages of Generating Seasonal Weather Forecasts

2.4.2 Deriving seasonal forecast relevant for Africa

One of the models for inter-annual atmospheric variability is the non-oceanic component of the El Niño/Southern Oscillation (ENSO), this can be traced back to Walker and Bliss (1932). Daily weather forecasts of specific rainfall events, associated with explicit synoptic rainfall producing systems, are accurate to only about *five days*. For a thorough regional analysis, *global data sets are required*, even for relatively simple multivariate statistical analysis.

The process of deriving a seasonal forecast (Washington, Downing 1999)

Seasonal forecast methods used to predict African rainfall are: (1) Statistical Analyses of Rainfall: the analysis of the rainfall time series of a region alone, without linking rainfall variability to the atmospheric circulation or underlying physical mechanisms; (2) Numerical Approaches: offers the largest potential for future improvement. The integration of General Circulation Models (GCMs), usually with sea surface temperature (SST) forcing, typically over a period of 50 or more days; (3) multivariate Empirical Approaches - the ability to predict seasonal rainfall totals several months in advance is due to the exchanges of energy between the oceans and the atmosphere, which includes the weather systems that produce rainfall. In practice, quantification of the interaction between the ocean and atmosphere in empirical studies typical of those which lead to forecasting schemes is assumed to be represented by sea surface temperature anomalies (SSTAs) alone and (4) numerical and Statistical Approaches

Table 2-5: Selected Operational Forecast for Africa

Area	Institute	Months	Methods	Inputs
East Africa	UKMO	Oct-Dec	Regression	SST
East Africa	University of Wisconsin	Sept-Dec	Neural Networks	SST + A
East Africa	NOAA	Oct-Dec	CCA	SST
Sahel	NOAA	Jul-Sept	CCA	SST
Sahel	CSU	Jul-Sept	Regression	SST + A
Sahel	UKMO	Jul-Sept	Regression + LDA	SST
Southern Africa	University of Witwatersrand	Jan-Mar	Regression	SST
Southern Africa	University of Zululand	Oct-Mar	Regression	SST + A
Southern Africa	University of Wisconsin	Jan-Mar	Neural Networks	SST
Southern Africa	South African Weather Bureau	Jan-Mar	CCA	SST

Notes: United Kingdom Meteorological Office (UKMO), National Oceanic and Atmospheric Administration (NOAA), Colorado State University (CSU), Canonical Correlation Analysis (CCA), Linear Discriminant Analysis(LDA), Sea Surface Temperature (SST), Other Atmospheric Variables (A)

2.5 Indigenous Knowledge versus Modern Science on Droughts

2.5.1 Complementary Role

Researchers (Mercer, Kelman et al. 2010; Mugabe, Mubaya, Nanja et al. 2010; Ziervogel, Opere 2010) today concur that indigenous knowledge and modern science complement each other. In Dondeyne, Emanuel et al. (2003), for example, bridging local farmers' and scientists knowledge through participatory research led to more appropriate technologies. It was a win-win arrangement where both parties learned from each other. So, do the modern approaches to drought prediction complement or contradict the African indigenous knowledge? First, the accumulated knowledge has always worked for the locals (Aparna, Trivedi 2011); the debate here can only be on the level of success. On the other hand, the western approaches to weather prediction are hardly utilised by the mostly illiterate farmers most of whom live in the remote villages where modern technologies such as televisions and internet are still a foreign concept (Luseno, McPeak et al. 2003; Grasso 2007; Mugabe, Mubaya, Nanja et al. 2010; Masinde, Bagula et al. 2012b). Secondly, implementing modern drought prediction technologies is still a costly affair for most African countries whose priority list is filled with items such as 'providing basic education', 'implementing democratic constitution', 'peace initiatives', 'providing basic healthcare', and so on. Installing a single modern weather station costs tens of thousands of Euros; moreover, qualified meteorologists are expensive to train and after all these, the disseminated weather information is unusable by the farmers.

There is lack of utilisation of seasonal forecasts by farmers (especially small-scale) in the developing countries (Hulme 1994; Blench 1999; Agrawala, Kenneth et al. 2001). Poor utilisation of scientific forecasts is mostly due to lack of accessibility, content format/syntax and timeliness of the forecasts. Farmers in Northern Kenya needed at least four to six weeks' notice of rainfall-onset (Luseno, McPeak et al. 2003) while in Burkina Faso, the farmers sought one to two full months prior to onset of the rainy season (Roncoli 2002). On the contrary, IK is cheaper and timesaving and no formal training is required. Sadly, this indigenous knowledge is now endangered by new and expanding hazards that are rapidly changing the living conditions in many places in the tropics and sub-tropics (Blench, Marriage 1999; Stigter, Zheng et al. 2005) as well as by events such as colonialism, western education system, globalisation, ICTs revolution and global warming. The ripple effect is that many traditional forecasting methods are perceived as becoming less reliable (Luseno, McPeak et al. 2003; Dekens 2007) and makes it is difficult to talk about it in isolation. To further compound the problem, most of the indigenous knowledge on droughts and indeed other domains have been eroded over the years; the younger, urbanised, educated generation does not know much about it. A survey among the Mbeere people for example indicated that the younger (below 25 years) and more educated people had less knowledge (than the older ones) on IK weather indicators. Online databases can certainly be used to conserve the little that is left. The twin-reality is that (1) indigenous knowledge is a valuable resource that must be embraced as one of the ways of countering the now more frequent and more serious extreme meteorological and climatological events; and (2) the conventional science of climate/weather forecasting must now more than ever before take a humane socio-economic angle; it must shift from being supply-driven to demand-driven (Roncoli 2006; Sabine, Elke et al. 2007; Mercer, Kelman et al. 2010).

Indigenous knowledge and modern science-based weather forecasts are not mutually exclusive but significant discordance between the two is still apparent. Clear understanding and careful integration of indigenous knowledge present opportunities especially in the dissemination process of weather forecasts to farmers in SSA because this will support ways that are culturally appropriate and locally relevant. There is a common departure that, generally (not just in climate and weather information), integrating indigenous knowledge into modern science can improve livelihoods (Brokensha, Warren. et al. 1982; Thrupp 1989; Flora 1992), Richards 1993; Virji, Cory et al. 1997; Sillitoe 1998). Some of the reasons that motivate promotion of IK are: (1) IK is already processed by the community; (2) by recognising and sharing the IK, the community feels valued and therefore confident to participate in risk reduction initiatives. This by extension ensures that they can immediately respond to potential risk and consequently leads to strengthened resilience and self-confidence (Mutua 2011).

On the question whether IK needs modern science, there is evidence that IK has been eroded and is slowly disappearing. Some of the factors leading to this include civilisation, religion and education. Extreme variations never seen before by community members bring IK into disrepute, and the current emergency (mostly donor-funded) responses such as relief food may change in future. Integrated approaches aimed at giving the communities several levels of risk-preparedness are desirable. On the other hand, using IKFs alone, it is difficult to forecast beyond a season, in modern science, this can be achieved by employing technologies such as ANNs. Some terminologies used in IK may sometimes have more than one meaning, for example ‘abundant rainfall’ may mean rainfall for the day or a season. Finally, unlike modern science, climate change may be difficult to foretell using IK alone.

2.5.2 The Differences and Similarities

The nature of IK is such that most of the indicators can be learned by anyone by way of listening to the older people as well as in the process of interacting with the environment during every-day activities. On the other hand, conventional science is knowledge generated by experts using recognised and rigorous approaches to observation and experimentation. In scientific weather forecasting, the meteorologists present forecasts as probability of seasonal rainfall being above, below or normal compared with historical trends. Production, dissemination and utilisation of these forecasts remain a challenge world-over; the challenge is more pronounced in Africa.

While scientific knowledge is global, indigenous knowledge is local. Both knowledge systems are dynamic; they are continually influenced both by internal creativity and experimentation, and by contact with external systems. They are also intertwined with power and human relationships raging from social to political and economic. Indigenous knowledge is more qualitative and geographically specific. The indicators used are usually so specific to a location; for instance, the quantity of fruits and flowers of some specific trees as a sign of rain or drought is common most of the knowledge systems but the farmers refer to specific tree in a specific place for instance near his farm (Roncoli, 2006). The level of water in a well among the Mbeeres would refer to a specific well in a specific village (Masinde, Bagula et al. 2012b). Local prediction provides clues about those aspects of climate that are most salient for farmers and about the kinds of climate information farmers seek to mitigate climate risk. Studies by for example Roncoli, Ingram et al. (2004) show that farmers view rainfall as a process rather than a quantity and as such, '*drier than usual season*' to a farmer means '*shorter than usual*' and not '*less rains*'. Seasonal climate forecasts express quantity rather than temporal parameters because tools used cannot reliably predict duration and distribution aspects of rainfall. The lack of appreciation (or and putting in consideration) the cognitive framework of users of climate information on one hand and the producers of climate information on the other hand often leads to misinterpretations or mistrust. For instance, farmers think in terms of shorter timeframe and localise scale, while the scientists look at the long-term global perspective (Hansen 2002; Sabine, Elke et al. 2007).

Table 2-6: Comparison between Indigenous and Scientific Drought Forecasts

Indigenous	**Scientific**
Use biophysical indicators of the environment as well as spiritual methods	Use of weather and climate models of measurable meteorological data
Forecast methods are seldom documented	Forecast methods are more developed and documented
Up-scaling and down-scaling are usually complex	Up-scaling and down-scaling are relatively simple
Application of forecast output is less developed	Application of forecast output is more developed
Communication is usually oral	Communication is usually written
Explanation is based on spiritual and social values	Explanation is theoretical
Taught by observation and experience	Taught through lectures and readings
Adapted to local conditions and needs	Formulated at a larger scale and lacks relevance at local level
Refers to rainfall duration and distribution and it is aligned to crop-weather indicators	Refers to rainfall quantity at a regional level
It is language based and qualitative	It is number-based
It is holistic – it covers large number of variables qualitatively	Covers small number of variables quantitatively
It is a way of live – looks at both the process of knowing and the knowledge itself. It is explicit in its social-context aspect and it is an integral part of people's culture	Has no social context
It has rules of the 'knowing process'	It is based on rules of science, that is evidence, repeatability and quantification

2.5.3 Integration Framework

Integration Initiatives

In order to develop sustainable strategies, it is therefore important to take into account of, and learn from, what local people already know and do, and to build on this. Scientific and indigenous knowledge systems have increasingly been accepted as two areas of expertise that complement each other. Over the last 10 years, initiatives to integrate the two systems has increased two-fold especially in the area of environment conservation (Krupnik et al., 2007; Lauler, Shankar 2008; Voinov, Brown, Gaddis et al., 2008; Rajaram, Ashutosh 2010; Voinov, Bousquet 2010). Though this integration has potential of bringing several benefits, the diverse nature of the two makes it a daunting task (Giordanoa, et al. 2011). For instance, IK is highly informal and tacit; it is often represented using vague linguistic variables (Sicat, Emmanuel, John, Carranza et al. 2005); on the other hand its scientific counterpart is explicit and highly structured (Giordanoa, et al,. 2011). If IK is to be integrated with the scientific knowledge and eventually be used in decision-making process, there is need to represent IK in some form of explicit-structured way; fuzzy logic is one way of achieving this. This is because other approaches that employ subjective and qualitative approaches may not capture the holistic nature of IK whose variables do not have precise non/membership

After observing a positive relationship between forecasts based on indigenous knowledge and those based on modern science, Mugabe, Mubaya, Nanja et al. (2010), recommended that the two knowledge systems should be integrated. Though not related to this recommendation, such an initiative[5], spearheaded by the IGAD (Intergovernmental Authority on Development) Climate Prediction and Applications Centre (ICPAC), was started in September 2008. The integration was geared towards maximising the strengths of the both forecasting systems and by extension to improve the adoption of weather forecasts by small-scale farmers in SSA. The project brought together meteorologists and the Nganyi indigenous knowledge forecasters to build 'reconciliations' between the two forecasting systems. The reconciled forecasts were

[5] Integrating Indigenous Knowledge in Climate Risk Management to Support Community Based Adaptation in Western Kenya http://www.africa-adapt.net/aa/ProjectOverview.aspx?PID=PUXVdbXh9bM%3D)

carried out for 8 seasons (September 2008, March 2009, September 2009, March 2010, September 2010, March 2011, September 2011 and March 2012) and results disseminated through the locally available (existing) communication channels such as chief *barazas* and churches. The outcome of the project has been rated 'very good' by the two parties. After September 2010, KMD committed resources to ensure the success of the project.

The interest of incorporating indigenous knowledge into scientific knowledge has been especially highlighted within small island developing states (SIDS), due to their inherent vulnerabilities and propensity to environmental hazards (Mercer, Kelman et al. 2010). In Papua New Guinea, in developing a *National Disaster Risk Reduction and Disaster Management Framework for Action 2005–2015*, the need to integrate traditional knowledge into disaster management systems was identified but not the how this may be achieved (Papua New Guinea National Disaster Centre 2005). There are several windows of opportunity to be taken advantage of in pushing the integration agenda; the power of the 'modern' view of scientific forecasts by people especially the younger generation is one such window.

Other integration initiatives have been carried out in the assessment of soil types classifications and soil fertility carried out in South-western Burkina Faso (Gray, Morant 2003), East Africa (Uganda and Tanzania) and Bangladesh (Payton, Barr et al. 2010) and in Nisamabad District of Andhra Pradesh State in India (Sicat, Emmanuel, et al. 2005). Using examples from Inuit and other northern peoples, another integration of IK with scientific knowledge is in analysing the complexity of ecological knowledge (Berkes, Mina 2009). In Verlinden, Dayot (2005), integration of the indigenous knowledge on the environment with the scientifically based vegetation analysis for north central Namibia is discussed. Krupnik and Ray (2007) tackle the integration in relation to subarctic marine ecosystems while Lauler, Shankar (2008) looked at the integration of ecological knowledge for marine habitat monitoring in Oceania. Krupnik and Ray (2007) compared scientific knowledge (marine biology and ecology) and the knowledge of indigenous hunters on walrus distribution, abundance, and life cycle to study climate change in the in the Beringian Region. In all these studies, there is a common conclusion that there are fundamental difference between indigenous and scientific knowledge systems and integrating the two results in more robust systems with the two complementing each other.

Such integration offers one way of dealing with the complexity of drought monitoring system (Pahl-Wostl 2007). However, efforts towards this integration are rare; his is the main contribution of the research work described in this thesis. From a two-year study in Goima Ward, Tanzania, (Slegers 2008) a comparison between the scientific agricultural droughts and farmers' indigenous knowledge and perception of droughts is presented. Other brief mentions of this integration are found in, Roncoli (2006), Mugabe, Mubaya, Nanja et al. (2010) and Orlove, Roncoli et al. (2009)

Integration Guidelines

A look at the conceptual framework that dictates how farmers perceive scientific climate information reveal serious discrepancies between what the farmer expects and what the scientific weather forecasters perceive as the farmer's needs; this leads to the famous, '*expectation-perception*' gap that often lead to failure of many innovation systems projects. Further, the dynamic nature of local cultural systems provides a point of intersection with scientific forecasts hence the departure that incorporating farmers indigenous knowledge into scientific forecasts can improve the farmers' ability to understand, appreciate and utilise the forecast information. Farmers' uptake of forecast information is not only influenced by what they know but also by what they believe, their prior assumptions and attitudes (Thompson, Scoones 1994). The integration could be driven by the following guidelines:

Using indigenous knowledge to Downscale Weather Forecast:; It is argued that new technology will be more easily introduced and assessed if the approaches build on existing indigenous knowledge, and an understanding of local problem solving, experimentation and innovation (1997). Downscaling of the coarse resolution seasonal climate forecasts outputs (300km) to determine the biological/hydrological effects at regional level (5 km), is crucial if weather forecasts are to find relevance among the small-scale farmers in SSA (Lau, Young et al. 1999). This is currently a daunting task for meteorological organisations charged with generating seasonal weather forecasts. This is because, in order to carry out effective weather forecasting, these organisations need to be equipped with a number of synoptic stations. These are stations that have the capability to observe and record all the surface meteorological data; rainfall, temperature, wind speed and direction, relative humidity, solar radiation, clouds, atmospheric pressure, sun shine hours, evaporation and visibility.

Climate monitoring is one of the main drought mitigation strategies. The latter is currently implemented in SSA using macro-infrastructures based on expensive and well-calibrated weather stations. The stations are then sparsely deployed by governmental organisations in form of relatively small number of fixed locations to provide climate maps for droughts and other natural disasters prediction. This creates a feasibility gap that needs to be addressed through complementary technologies, systems and strategies. With this kind of sparse network, it is not possible to provide locally relevant information necessary for scaling weather information down to the local (say village level) communities (Masinde, Bagula et al. 2012a). Why not incorporate the IK to fill this gap?

Scaling-Up Indigenous Knowledge **-** It is crystal clear that there are more similarities than difference in the indigenous indicators used to forecast weather/climate/droughts across Africa, the ability to port one indigenous weather forecasting utilisation success story across other communities in SSA is a key to the success of the integration. However, this is currently an up-hill task; first, some aspects of the IKFs are based on myths and religious beliefs that may not apply across communities. Two, the common aspects of the IK observational such as observing flowering patterns trees and positions of the sun/moon/stars, have not been formally (say in a searchable database) documented anywhere. An integration framework must be designed to cater for this

Integrating the forecasts into user applications: Given that indigenous knowledge is based on relative and local experience, it lacks benchmarking techniques hence making it a big challenge to harmonise and integrate it within the conventional forecasting systems. However, given the potential of this knowledge, researchers cannot give up on the integration initiative. This led Aparna, Trivedi (2011) to recommend integration as a way of enhancing accuracy and reliability of SFCs in the face of climate change. One avenue of achieving this is by integrating the indigenous and scientific forecasts into user applications (Caio, Simone 2010).

2.6 Early Warning System for Droughts

2.6.1 Definitions

In Richard-Van, Gaëlle et al. (2011), ***early warning (EW)*** is defined as "*the provision of timely and effective information, through identified institutions, that allows individuals exposed to hazard to take action to avoid or reduce their risk and prepare for effective response*." Disasters emanating from meteorological, hydrological and climate hazards are known to cause massive loss of lives and property alike; these disasters have dramatically increased (up to 50-fold) over the last 50 years. For instance, such disasters were responsible for over 70% of the over 2 million people killed by global disasters that took place between 1980 and 2007. Luckily, the vigour with which early warning systems for such disasters has been tacked has ensured that the losses, (especially of lives) associated with them have decreased by over 97% (Richard-Van, Gaëlle et al. 2011). This gives an indicator of the critical role played by accurate, effective and relevant early warning systems for disasters triggered by extreme climate variations.

Effective early warning systems consist of four components; (1) gathering of the risk knowledge; (2) monitoring and predicting the situation; (3) communicating the warning messages; (4) responding to the warning ISDR 2006). The phenomenal role of ICTs in all the four components cannot be overemphasised; this include remote sensing that enables real-time detection of hazards, Short Message Service (SMS) technology that allows for direct and individualised delivery of disaster alerts and the instantaneous access of diverse and voluminous information via the Web, just to mention a few.

2.6.2 Existing Drought Early Warning Systems

An inventory of the early warning systems existing globally revealed that due to the complex nature of droughts, early warning systems for droughts are the least developed and very few systems in this category exist (Grasso 2007). Current systems that address droughts are multi-hazard and drought is just a small component of the entire system. One example of such systems relevant to Africa is the Famine Early Warning System (FEWS Net), which provides monthly reports on famine and droughts in Eastern Africa (among other regions). There is no one single early warning system (known to the author) dedicated to tackling droughts in Africa. Other such systems described by (Grasso 2007) are: Global Information and Early Warning System on Food and Agriculture (GIEWS) by Food and Agriculture Organisation (FAO), and Humanitarian Early Warning Service (HEWS) by World Food Programme (WFP) both of which target global users. At national levels, the U.S. Drought Monitor is the best-known drought early warning system, while the most relevant (to this research) system is the East Asian drought monitoring system that makes use of the Effective Drought Index to describe the spatial and temporal distribution of droughts in East Asia (Republic of Korea, Democratic People's Republic of Korea, Japan, and China) (Oh, Do-Woo et al. 2010).

2.6.3 People-Centred Approaches to Early Warning Systems

Several authors (UN Secretariat General 1994; Cocchiglia 2007; Deely, David et al. 2010) have identified *people-centred approaches* as one avenue for delivering a relevant, effective and sustainable early warning system for droughts. One such initiative entails mobilising the local communities to participate in running such a system by incorporating their rich indigenous knowledge on droughts, allowing them access to the system (input and output) using their mobile phones and by proving drought alerts in syntax and semantics that they can comprehend.

3. Research Methodology and Design

"Discovery consists of seeing what everybody has seen and thinking what nobody has thought" (Albert Szent-Gyorgyi)

Falsificationism is the idea that science advances by unjustified, exaggerated guesses followed by unstinting criticism. Only hypotheses capable of clashing with observation reports are allowed to count as scientific (Popper 1959).

3.0 Introduction

In his work titled; "*What is this thing called science?*" Chalmers (1982) summarised Popper's position (Popper 1959) as follows: *Science starts with problems, problems associated with the explanation of the behaviour of some aspect of the world or universe. Falsifiable hypotheses are proposed by scientists as solutions to the problem. The conjectured hypotheses are then criticized and tested. Some will be quickly eliminated. Others might prove more successful. These must be subject to even more stringent criticism and testing. ... It can never be said of a theory that it is true, however well it has withstood rigorous tests, but it can hopefully be said that a current theory is superior to its predecessors in the sense that it is able to withstand tests that falsified those predecessors.* (pp 45)

In this thesis, we identified a problem; the drought/weather forecasts systems (mostly Seasonal Climate Forecasts) currently in use in Sub-Saharan Africa are not reliable, not useable and certainly not relevant to the context of the small-scale farmers in this Region. In line with Popper's Critical rationalism, we proposed a falsifiable hypothesis to solve this problem: "*people-centred drought early warning systems can empower people at the local level. Such systems increase people's sense of ownership and confidence in using the systems. Consequently, the people become more resilient to the droughts and are able to protect themselves".* In the Sub-Saharan African context, one way of achieving this is by incorporating African indigenous knowledge on droughts, exploiting the widely available mobile phones and employing Wireless Sensor Networks (WSNs) to collect micro/local droughts data.

This chapter therefore captures the details of how (the research methodology) we went about testing this hypothesis. In Kumar (2005), the term research is defined as "*a structured enquiry that utilises acceptable scientific methodology to* *solve problems and create new knowledge that is generally applicable."* The level of formality, rigorousness, verifiability and general validity determines the degree to which a research method can be said to be scientific. Research can be classified based on: (1) Research application (pure or applied); (2) The objectives of carrying out the research descriptive, correlational, explanatory or exploratory); (3) Research's inquiry mode structured or unstructured). Driven by the objectives, hypotheses and research questions described in Chapter 1, our research took the following three approaches:

i. **Applied-descriptive-structured** research carried to analyse the characteristics and patterns of drought patterns in Kenya. It was also applied in describing the various aspects of indigenous weather forecasting systems;

ii. **Applied-correlational-structured** research was used to discover the similarities and difference between the modern science and indigenous ways of forecasting weather. This was also used to test the field-readiness and acceptability (by meteorologists) of wireless sensor-weather meters for measuring weather parameters;

iii. **Applied-exploratory-unstructured** was used for all other aspects of the research presented here. This was informed by the fact that the wireless sensors technology is relatively new in the context (Sub-Saharan Africa and weather monitoring) of its application in our research and that three very diverse domains (Computer Science, Meteorology and Indigenous Knowledge) were traversed in the course of the research. It was applied in investigating the suitability of Effective Drought Index (EDI) and Artificial Neural Networks (ANNs) in qualifying/quantifying and forecasting droughts respectively. The approach was also used in evaluating the effectiveness of ICTs (mobile phones, wireless sensors and intelligent agents) in developing an effective Drought Early Warning System (DEWS) for small-scale farmers in Sub Saharan Africa (SSA). Finally, we used this approach to investigate the suitability of fuzzy logic in capturing and representing the holistic nature of indigenous knowledge.

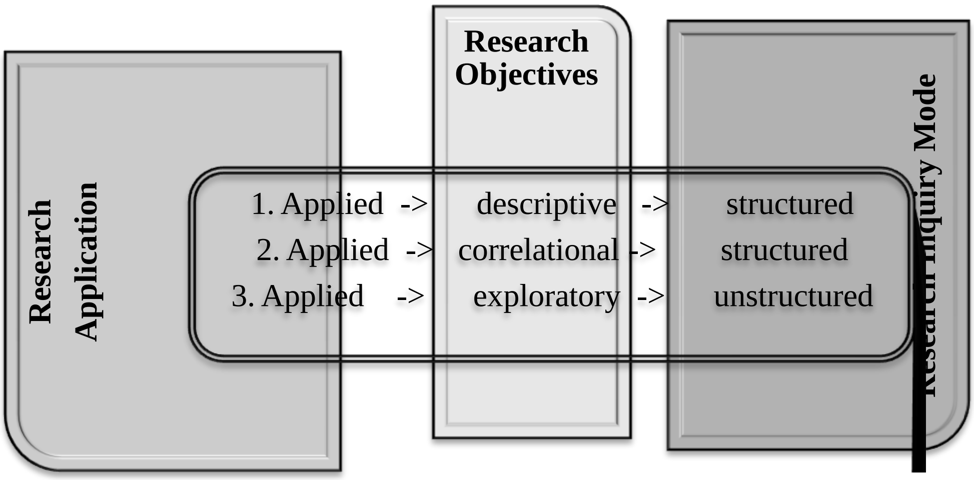


Figure 3-1: Research Approaches Applied

3.1 Research Design

Research design is the conceptual structure within which research would be conducted; its function is to ensure that the evidence obtained enables the researcher to answer the research question(s) as unambiguously as possible (Vaus, 2001). Guided by the objectives described in Chapter 1, *Experimental* and Case Study research design approaches were selected. Further, the following aspects of the research were also evaluated before deciding on these two research design approaches: (1) The number of groups in the design; (2) Number of pre-tests and/or post-tests measurement phases; (3) Method of allocation of cases to groups; and (4) Nature and/or number of interventions.

Experimental Design was applied in the testing of the field readiness and the calibration (against professional weather station) of the wireless sensors-based weather stations;

Case Study Design was applied in the validation of the following hypothesises:

i. Effective Drought Index (EDI) can be used to qualify and quantify droughts in absolute terms

ii. Artificial Neural Networks (ANNs) can be used to accurately forecast droughts

iii. The occurrence of an extreme climate event (drought or flood) during the October-November-December rain season in Kenya increases the probability that a similar event will occur during the March-April-May rain season

iv. Integrating IK with SFCs and disseminating the resulting forecasts through mobile phones in the local languages leads to improved utilisation of the forecasts.

3.1.1 Experimental Design

Surveys and experiments are the prime examples of quantitative research. For our research, we chose experiments as the suitable design for calibrating the weather sensors. Novel experiment types called ***Recursive Participatory Experiments (RPE)*** were used. Customised forms of these experiments were also employed in two (use of EDI and ANNs in assessing and forecasting droughts) phases of the case study design. Our experiments model entailed running a series of **Pi**lot, **E**xploratory and **C**onfirmatory **E**xperiment**s** (PiECEs) recursively. After every cycle, the stakeholders (meteorological departments, indigenous weather forecasters and farmers' representatives) were given a chance to evaluate the solution (Participatory) before other cycles of PiECEs were executed. For instance, before employing sensors as weather stations, a series of PiECEs were performed in consultation with KMD. A similar approach was performed in determining the best parameter (rainfall, humidity, temperature, pressure, IK indicators) combination for use in developing an ANNs-based drought-forecasting tool.

Pilot Experiments are small, usually short-term, experiments, which are used to test the logistics of a proposed study with the aim of gaining preliminary information. Pilot experiments are common approaches to environmental action and are used to test novel practices or technologies (Billé 2010). In the current work, before leaving the sensor nodes in the field for long periods of time, pilot experiments were first carried out in order to give an indication of how the various sensors' components behaved. On the other hand, **Exploratory Experiments** are used to study the patterns of response to some parameter variations or intervention, without necessarily being based on a formal hypothesis, and may be used to generate hypotheses for more formal testing in confirmatory experiments. After pilot and exploratory experiments, **Confirmatory Experiments** were carried out to clearly test the hypothesis that was set prior to the commencement of the all the experiments (Franklin 2005; Festing 2012).

During our experiments, the Participatory Phase (Evaluation by Stakeholders) was carried out soon after the Pilot and Exploratory Experiments in some cases. In the figure below this is represented by path ***1b*** and ***2b*** respectively. This was necessary in scenarios where the experiments were outside our respective domains such as the interpretation of IK weather indicators. This was to avoid running the full cycle of experiments (PiECEs) without involving the stakeholders. The path ***4b*** allowed the 'return to normal' PiECEs' cycle; that is resume Exploratory Experiments interrupted by path ***2b***.

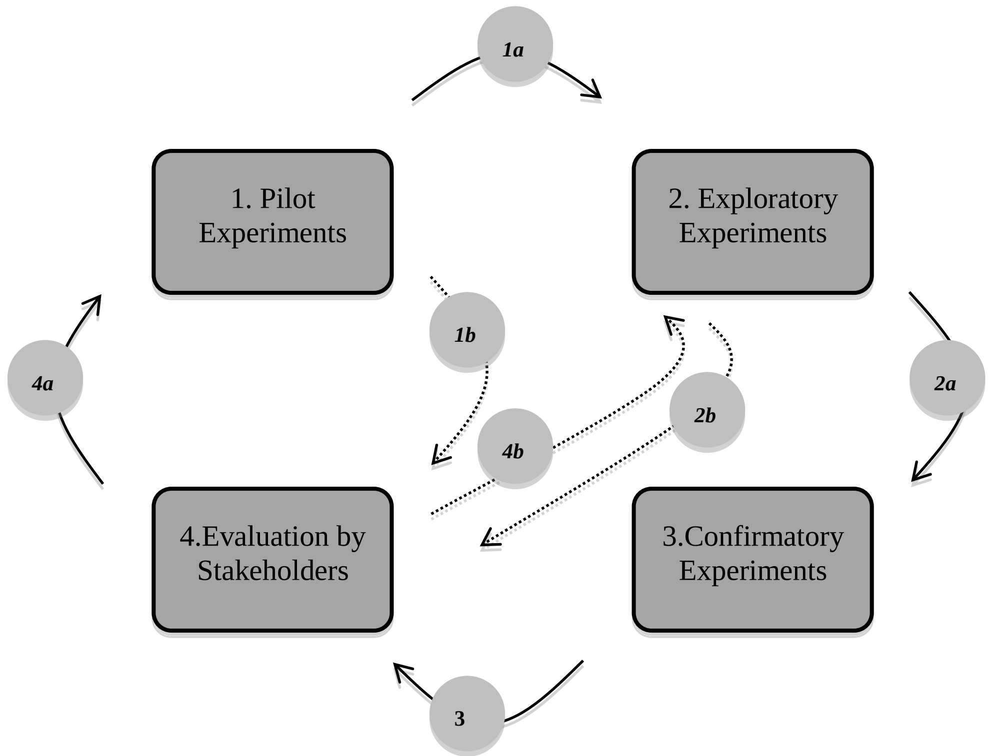


Figure 3-2: The Phases of PiECEs Experiments Model

Exploratory Experiment Cycles

The overall objective of this research introduced three levels of complexity: (1) Wireless Sensors are relatively new technology especially for weather monitoring; (2) Indigenous knowledge is highly holistic and some of its aspects are intertwined with the communities' myths and religious beliefs; (3) Use of mobile phones as the main computing device ensures that the resulting system inherits all the inherent challenges[6] of this tiny device. The exploratory experiments (not guided by hypothesis) approach came in hardy because they allowed for testing not just the hypothesis but also determine whether the various components of the integrated solution were working properly in different conditions. For instance;

i. The sensors' GSM/GPRS module could be affected by the strength of the GSM network signal available in a region;
ii. The indigenous weather forecast indicators that are of metrological nature (for example, 'strong wind blowing from East towards Lake Victoria is a sign of bad season') could be validated using weather sensors.

With all these angles and twists to the experiments, the exploratory experimentation was recursively carried out until all issues were resolved. In developing all the various system modules that make up the integrated DEWS, the exploratory experiments involved:

i. The design of computer programs (code that implements the system module) using Prototyping;
ii. System Deployment;
iii. User (Evaluation by Stakeholders) Testing;
iv. System monitoring, evaluation and testing of theories and use them to adjust various variables in the system program code.

For each of the modules, several cycles of the above steps were carried out as show below:

[6] Examples include Highly mobile; reliance on battery power that gets drained fast; hardware and software heterogeneity and highly personalised

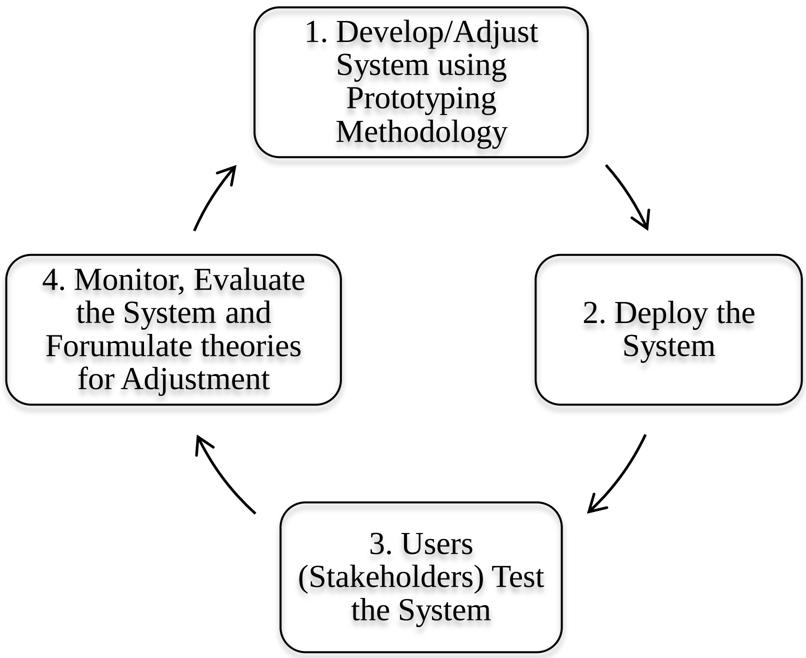


Figure 3-3: Exploratory Experiment Cycles

Prototyping

In Patton (1983) and Ratcliff (1988) **prototyping** is defined as "*the process of developing a trial version of a system a prototype) or its components in order to clarify the requirements of the system or to reveal critical design considerations*". As explained in Kemerer (1996), there are many reasons for adopting prototyping in systems' development. Two that are relevant to this research are: (1) To allow both the developer and the users to continuously test the system and ensure that the final system is what is required; (2) To allow the developer understand the technical aspects of the system as well as test its feasibility. In this research four system modules were developed and later integrated to form the integrated DEWS. Each of the modules was separately developed using prototyping; the process of interacting the modules into one system followed prototyping method too.

i. **Programming sensor weather boards** – for this, Waspmotes by Libelium[7] were used. Programming the sensors involved writing various pieces of code using the latest (at the time of the research) Waspmote(IDE. The code would then be uploaded and executed on the sensor boards;

7 http://www.libelium.com/forum/index.php

ii. ANNs Drought Forecaster – this is made up series of ANNs network models designed and executed in MATLAB and deployed using a web-interface
iii. Fuzzy Indigenous Knowledge Drought Forecasting System – this too was built using MATLAB to represent the various aspects of IK on drought forecasting;
iv. Agent-Based IKFs and SCFs Integrator – this is a system prototype that implements the integration of the various system modules that make up the integrated framework. The Multi-Agent-Systems approach was used as realised in Java Agent DEvelopment (JADE) Framework (Bellifemine, Giovanni et al. 2004).

3.1.2 Case Study with Experimental Design

Yin (1984) defines case study approach as an empirical enquiry that '*investigates a contemporary phenomenon within its real life context, when the boundaries between phenomenon and context are not clearly evident and in which multiple sources of evidence are used*'.

The case study design was used to analyse historical daily weather data for over 30 years for four weather stations in Kenya. First it was used to determine if EDI could be used to qualify/quantify droughts and two, to investigate the suitability of ANNs in forecast droughts. The design of the case studies followed a model similar to the PiECEs described earlier. This led to the variation of Case Study with Experimental Design as shown in the figure below. Each of the case studies started off with a detailed Pilot-Single Case Study of one weather station followed by recursive Exploratory Multiple Case Studies of two weather stations. In the last phase of the case study design, detailed Confirmatory Single Case Study using data from the fourth weather station was used.

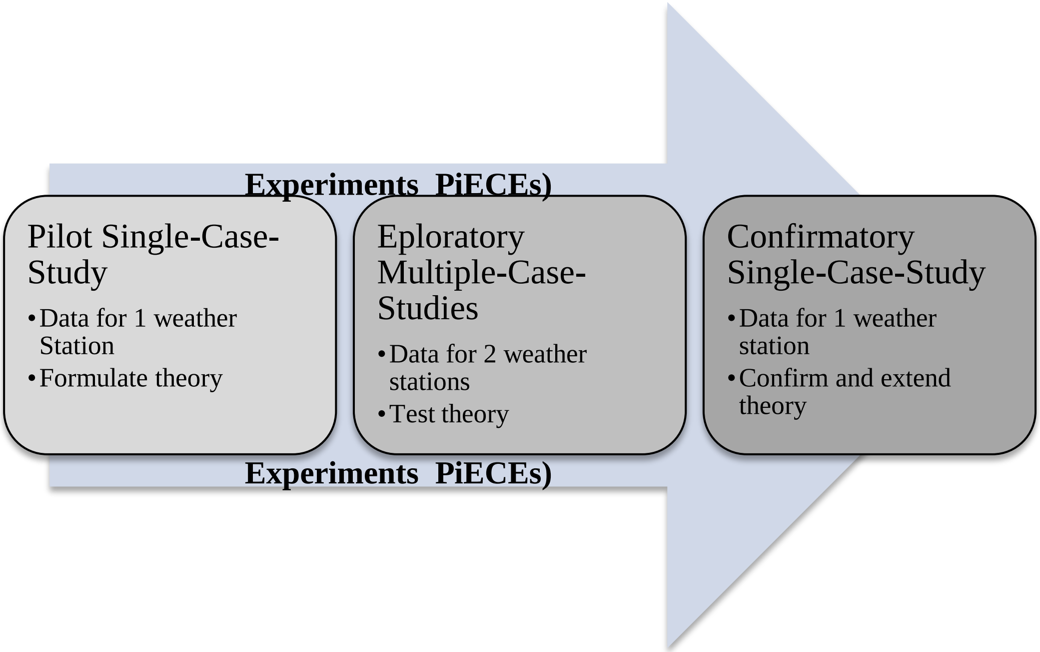


Figure 3-4: Case Study with Experimental Design

Descriptive case studies of indigenous weather forecasting systems were also carried out for following the Bunyore and Mbeere communities in Kenya. The objective here was to uncover the similarities/uniqueness of the various IKFs found in different communities. This knowledge later informed the development of the Fuzzy Indigenous Knowledge Drought Forecasting System as well as the Integrated DEWS.

3.2 Data Collection Methods

The following data collection methods were used for each of the two research designs described above

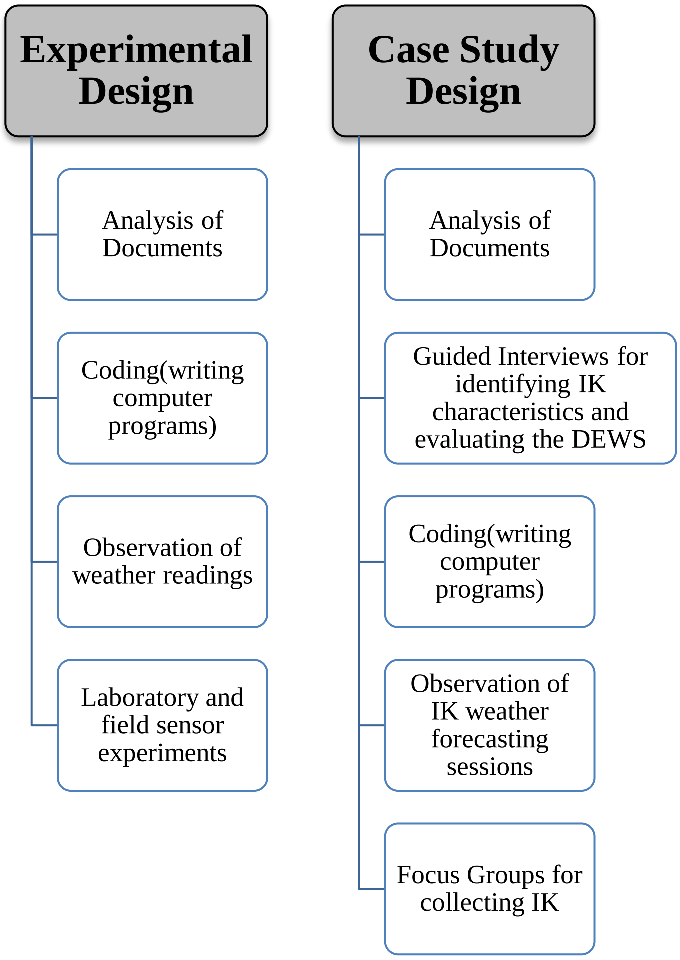


Figure 3-5: Data Collection Methods Used

3.3 Data and Error Analysis Methods

3.3.1 Calibrating for Uncertainty of Meteorological Measurements

From the perspective of sensor calibration, ***an error*** in the sensor reading is the sensor reading minus the equivalent (say temperature) reading from a weather station instrument. The closeness of these two values defines the ***accuracy*** of the sensor. On the other hand, the ***uncertainty*** of a sensor is the numeral expression of its accuracy; for example, a humidity sensor with accuracy of ±1.5% has an uncertainty of 1.5. During the calibration exercises, two types of errors may reveal themselves; ***systematic*** and ***random errors***. Random error represents stochastic fluctuations in measurement values when the measurement is repeated under identical conditions. In Dorsey, Eisenhart (1953) "*systematic error is used to cover all those errors which cannot be regarded as fortuitous, as partaking of the nature of chance. They are* *characteristics of the system involved in the work; they may arise from errors in theory or in standards, from imperfections in apparatus or the observer, from false assumptions, etc.*"

In Phillips, W. et al. (2001), one of the methods used to report the accuracy of calibration results is the '***Estimated Systematic Error and Uncertainty***' where the reported estimated systematic error is later used to provide a correction value used in subsequent measurements. This is the approach that was favoured in the current research because the aim was to calculate the correction factor to be applied on the sensors before deploying them as weather stations. Once the uncertainty value for a given sensor is established through calibration, the true value can be computed as follows:

<true value> = <measured valued> ±< uncertainty >

The true value is then used to carry out other calibration conditions such as:

i. ***Repeatability*** – how close are the results of successful readings (under the same conditions) from the sensors and
ii. ***Reproducibility*** – same as repeatability but under different conditions.

The values of the above are determined by inherent characteristics of the sensor boards such as: sensitivity, discrimination, resolution, hysteresis, stability, drift, and response time. In real-life applications, several sensors share one board and the sensors may depend on each other. In the experiments described in this research, the GPRS sensor was used by other (temperature, humidity and pressure) sensors to transmit readings to a database. The long and varied response times of this (GPRS) sensor, for example, affected the other sensors leading to ***lag errors***[8] in the readings' observation times.

Systematic Errors in Sensors

As per the PiECEs model described above, the calibration experiments followed a 3-steps experimental process with three types of experiments namely **pilot experiments**, **explanatory experiments** and **confirmatory experiments**. We also applied a systematic error analysis based on three error types: **Mean Absolute**

[8] The error that a set of measurements may possess due to the finite response time of the observing instrument

percentage Error (MAPE), **Mean Error (ME)** and **Root Square Error (RSE)** (Bissell, Chapman, 1992). We also checked for inherent errors that come with the sensor boards. **Correlation coefficients** and **plots** such as side-by-side boxplots were used to run **similarity tests** between various datasets.

Systematic Error Analysis was intended to estimate the error rates between the readings from the sensor nodes and those from the professional weather station. Datasets consisting of hourly readings (temperature, humidity and pressure) from sensor nodes on one hand and readings from the weather station on the other hand were plotted against time (0 GMT, 2 GMT…23 GMT). Taking the Weather Station Readings as the reference points, the following 3 types of error analysis were carried out using both MS. Excel and R statistical tool.

(i) **Mean Absolute Percentage Error** (**MAPE)**

Mean Absolute Percentage Error (MAPE) is a measure of accuracy in a fitted time series value in statistics, specifically trending, (Armstrong and Fred, 1992; (Bissell, Chapman, 1992). It usually expresses accuracy as a percentage, and is defined by equation 3-1:

Equation 3-1: Mean Absolute Percentage Error (MAPE) Equation

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| * 100$$

In our case, A_t was the reading from the weather station and F_t from the sensor

(ii) **Mean Error (ME)**

This was computed using equation 3-2

Equation 3-2 Mean Error ME) Equation

$$ME = \frac{1}{n}\sum_{t=1}^{t=n} F_t - A_t$$

(iii)**Root Mean Square Error (RMSE)**

To compute RMSE, the residuals and squared residuals) are first computed as follows: The difference between the readings from the weather station (A_t) and those from the sensor node (F_t) taken at time t (say, 0 GMT, 1 GMT, …,23 GMT). The average and then the square root of the squared residuals then computed. All this is carried out using equation 3-3.

Equation 3-3: Root Mean Square Error (RMSE) Equation

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{t=n}\left(F_t - A_t\right)^2}$$

Sensor Boards' Inherent Errors

i. **Sensor Vs. Board Temperature Differences**

Like many other sensor boards, the Waspmote board used in our experiments comes with an in-build function (***RTC.getTemperature);)***for measuring temperature. It was observed that the readings given by this function were consistently/uniformly higher than those given by the temperature sensor. Computing these differences formed a candidate basis for validating the temperature sensor readings; it emerged that there was an almost ***constant error*** [9] (readings difference) for all readings.

ii. **Lag Errors**

Weather observation times are standardised world-over through the World Meteorological Organisation (WMO). Hourly readings are only acceptable if taken within 15 minutes to the hour or at the hour (Jarraud 2008). For instance, valid readings for 0 GMT are taken any time between 23:45 and 00:00. As such, the readings taken by the sensors during the experiments had to conform to these timings. However, the sensors experience some various forms of delays such as GPRS connection time and I/O (SD Card) operations. With this in mind, all these delays needed to be computed in order to determine the appropriate 'sleep durations' for the sensor boards.

---

9 Same error for all every readings set (board and sensor temperature)

iii. **Similarity Tests**

In order to determine how close the readings from the sensors were to the reference (from professional weather station) **Correlation Coefficients were computed**

Aggregating Sensors Readings

The sensors were programmed to take readings every 30 minutes while the readings from the weather station were taken on hourly basis. That is, at hour ***t*** (say 1 GMT), the sensor boards recorded two readings for each of the sensors. For example, with 6 sensor boards, each fitted with 3 sensors (temperature, humidity and pressure), this would result in 12 readings for temperature, 12 readings for humidity and 12 readings for pressure. In order to aggregate these readings for the purpose of comparing them with the respective readings from the weather station, two options were pursued:

Option 1: Average All Sensor Readings Taken Within the Hour:

$$S_s = \frac{\sum_{1=1}^{n}(S_{i,1} + S_{i,2})}{2n}$$

Where S_s is the aggregated reading for Sensor S; for example, S could be temperature sensor or humidity sensor. S_{i1} and S_{i2} are the sensor reading for Sensor S on Sensor Board i. For instance, in the case of **five** sensor boards, the aggregated reading for **temperature sensors** would be computed as follows:

$$\mathbf{T_s} = \frac{T_{1,1} + T_{1,2} + T_{2,1} + T_{2,2} + T_{3,1} + T_{3,2} + T_{4,1} + T_{4,2} + T_{5,1} + T_{5,2}}{10}$$

Option 2: Average Readings Taken Closest to the Hour

In this case, only one out of the two sensor reading from each sensor board is considered; the one closest to the weather station readings' observation time. That is:

$$S_s = \frac{\sum_{1=1}^{n}(S_{i1})}{n}$$

In the case, given five sensor boards, the aggregated reading for the temperature sensor would be:

$$T_s = \frac{T_1 + T_2 + T_3 + T_4 + T_5}{5}$$

3.3.2 Ranking ANNs Models' Performance

In the case of ANNs that were designed to forecast droughts, regression (R) and Mean Square Error (MSE) were mainly used to select the networks models with the best performance. RMSE and Percentage RMSE were then used to determine the implications of the errors and the resulting forecasts.

i. **Regression Analysis**: the higher the value, the higher the rank because it is the measure of the correlation between the inputs and the outputs.

ii. **Mean Square Error**: the smaller the value the better the network; it is the average squared difference between outputs and targets. However, the value is bound to be directly proportional to the size of the outputs values. For example, the outputs/targets for Networks 15 to 21[10] are those of AWRI whose mean is **194.58** while for Networks 7 to 14 are for EDI values that ranges between -2.28 to 4.32 (an absolute mean of **±0.76521**).

iii. **Root Mean Square Error (RMSE)** - In order to get the actual implications of the networks, the Root Mean Square Error (RMSE) and the Percentage of the RMSE were computed.

[10] For more details on Networks 7, 11, 14 and so on, see Chapter 7

4. ITIKI's Architecture

Disasters are first and foremost a "local" phenomenon. Local communities are on the frontlines of both the immediate impact of a disaster and the initial, emergency response, which, experience has shown, is crucial for saving the most lives.

(Cocchiglia 2007, *page v)*

4.0 Introduction

In line with the overall goal of this research which is to provide a tailor-made solution for countering the devastating droughts that revenge the Sub-Saharan Africa, we present the solution architecture in this chapter. Dubbed the '*Integrated Drought Early Warning System (DEWS) Architecture*'; the framework provides the blue-print for the implementation of the system that integrates ICTs with the indigenous knowledge on droughts. First, an overview of the Framework's unique characteristics (relevance, affordability, sustainability, integrated, resilience, usability, effectiveness, generic, and micro-level) are presented followed by a detailed explanation of how each of the components aids in achieving these characteristics. Part of this chapter also is a detailed explanation of the critical role of three ICTs (mobile phones, wireless sensor networks and artificial intelligence) in oiling the Framework. Lastly, we briefly explain how we managed to extend the use of mobile phones to a computing device using two of our novel contributions; MobiGrid and MobiSoc.

4.1 General Elements of an Early Warning System

Effective early warning systems consist of four components; (1) gathering of the risk knowledge; (2) monitoring and predicting the situation; (3) communicating the warning messages; (4) responding to the warning ISDR 2006). The phenomenal role of ICTs in all the four components cannot be overemphasised; this include remote sensing that enables real-time detection of hazards, Short Message Service (SMS) technology that allows for direct and individualised delivery of disaster alerts and the instantaneous access of diverse and voluminous information via the Web, just to mention a few. The fourth component involves actual response to a disaster such as relief food and evacuation of victims; this is out of scope of this research.

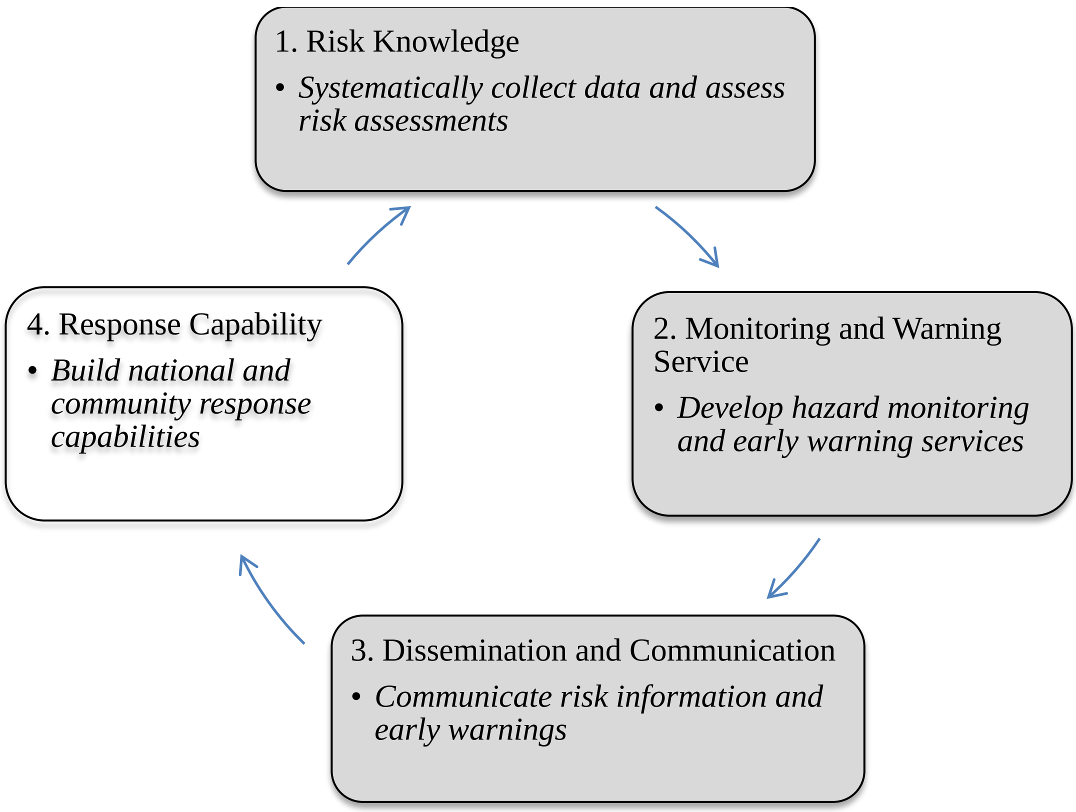


Figure 4-1: Elements of an Early Warning System

The remaining discussion on the above elements does not include Element number 4. The latter mostly requires resources and measures (for example, distribution of relief food, planting materials and so on) that are beyond the scope of our work. In order to incorporate WSNs, mobile phones and IK in our 3-Elements EWS, the above model was adapted as shown below (Figure 4-2).

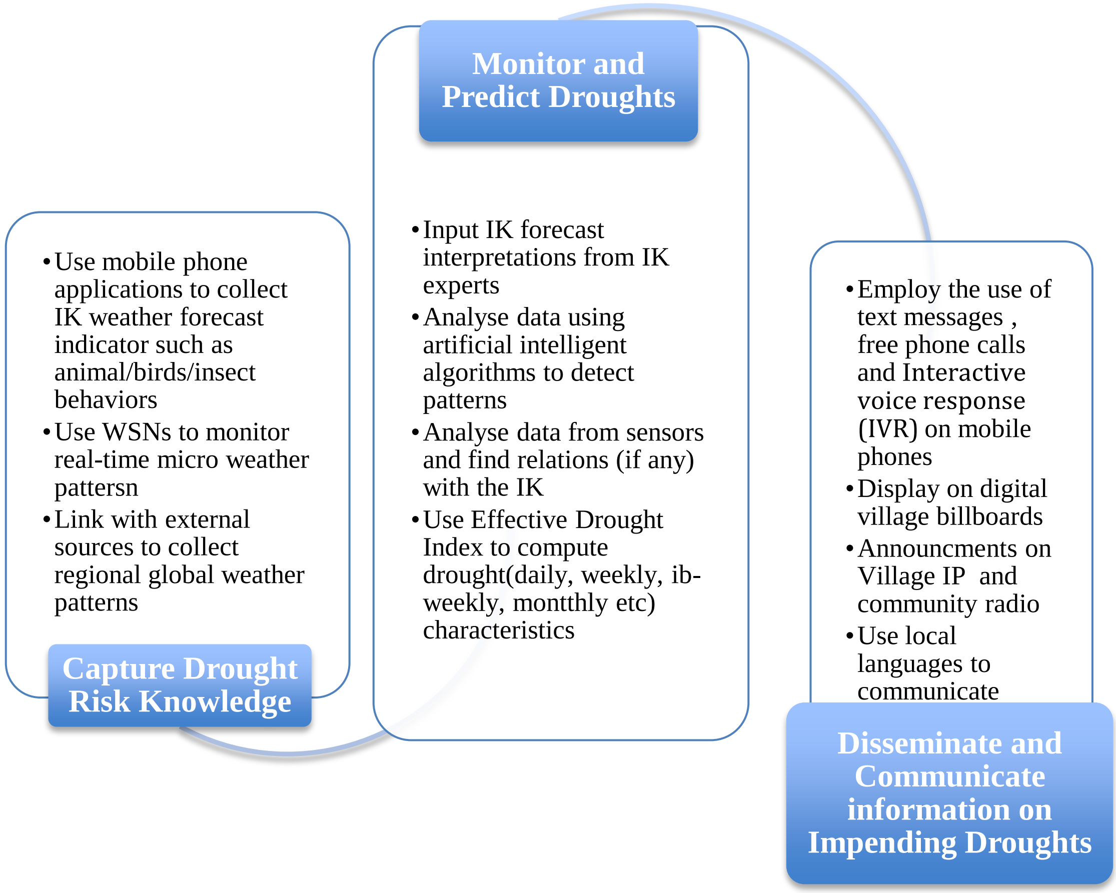


Figure 4-2: Extended Elements of an Early Warning System

4.2 Features of an Integrated Drought Early Warning System

The overall goal is to come up with a ***relevant***, ***affordable***, ***sustainable***, ***integrated***, ***resilient***, ***useable***, ***effective***, ***generic***, and ***micro-level*** early warning system for droughts for the Sub-Saharan Africa and Africa at large. Below is how each of these attributes is achieved in our integrated framework:

4.2.1 Indigenous Knowledge

Going by the phrase by Stern (1999), "*The effectiveness of forecast information depends strongly on the systems that distribute the information, the channels of distribution, the recipients' models of understanding and judgment about the information sources, and the ways in which the information is presented*." One way of achieving an ***effective*** early warning system for droughts is therefore to put into consideration the targeted users' coping strategies, cultural traits and specific situations. In the case of the Sub-Saharan Africa, this can be achieved by innovatively incorporating the local people's indigenous knowledge on weather/climate forecasting (Brokensha, Warren. et al. 1982; Fernando, Jayawardena et al. 1998; Sillitoe 1998; Orlove, Roncoli et al. 2009). The communities have accumulated a wealth of experience and information regarding prediction, reaction and recovery from drought. DEWS that incorporate IK automatically gains acceptability and sense of ownership among the people and the fact that such systems are built on what is known to have worked locally, makes them resilient (Mutua 2011). In order to incorporate IK into our framework, the first step was to harvest the immense IK lodged within the communities using software applications designed to work on the readily available mobile phones. This knowledge is then stored in a database from where it can be accessed for various uses; in our case to monitor and predict droughts.

4.2.2 Effective Drought Index

As the name suggests, the Effective Drought Index (EDI), by Byun, Wilhite (1999) is a ***very effective*** index compared to other drought indices. Its uniqueness stems from the fact that it provides spatial and temporal distribution of droughts on a daily-basis. As discussed in details in the in Chapter 6, EDI computes the intensity of droughts by using cumulative precipitation as a weighting function of time and also gives the Available Water Resources Index (AWRI); the latter is a measure of hydrological drought and can be used to assess the quantity of soil moisture. By incorporating it into our drought early warning system framework, it makes it possible to ***quantify and qualify droughts in micro scale*** (time and spatial distribution) as well as in ***absolute terms***. Our framework is able to accurately monitor the magnitude of on-going and past droughts using four dimensions (1) onset; (2) severity; (3) duration; (4) termination. Using historical data, it is also possible to use EDI to determine the probability of a drought occurrence in a given region.

4.2.3 Wireless Sensor Networks

A deeper look into the problem of early warning system for droughts in SSA reveals a grave situation where the meteorological institutions the National Meteorological Services (NMSs) charged with weather forecasting rely on weather stations that are thousands of kilometres apart (Jarraud 2008; EAC 2008). This sparse network creates a visibility gap that makes it difficult to provide locally relevant information necessary for scaling weather information down to the local say village level) communities. Furthermore, weather stations are very expensive and their operation may be difficult to sustain in many developing countries where the lack of expertise and high cost of maintenance may hamper operation after funding from donors. In our framework, the now readily available versatile and ***Wireless Sensor Networks*** (WSNs)-based weather stations are employed to fill the gap. This enables ***affordable*** and ***self-sustainable operation*** in developing countries. When deployed in their thousands, they can enable capturing of weather parameters at ***micro-level*** and hence downscale the forecast to a few meters making the drought monitoring and alerts relevant at the local level (Masinde, Bagula et al. 2012a).

4.2.4 Mobile Phones

The developing countries of Africa continue to experience various forms of 'digital divides' (University of Manchester's Centre for Development Informatics, ICT4D Blog 2011)one of them being the inability to offer information systems in basic sectors such as health and education. Although still experiencing a mobile phone penetration lag[11] of close to 10 years, Africa has achieved an average penetration level of 41% (ITU 2010a) which is much higher than that of computers. For instance, according to Kenya's 2009 population sensors (Kenya National Bureau of Statistics 2009), only 3.6% of households owned at least one computer in comparison with 63.2% of households that owned at least one mobile phone. With well-designed solutions, the use of these phones can be extended from the traditional use, as mere communication devices, to computing devices on which the much needed e-applications can be executed. Our DEWS utilises this window of opportunity by using the mobile phone to not only disseminate drought alerts but also as an input device for the IK. This way, the system is both ***affordable*** and ***sustainable***.

[11] The time gap between mobile phone penetration level in Africa, and the year that same level of penetration was achieved globally

4.2.5 Artificial Intelligence

Drought prediction is already complex enough; to add this complexity; our approach incorporates the use of IK, natural language processing, text-to-speech technologies and massive micro data read from wireless sensors. In order to create an ***integrated*** system that can juggle all these myriad moving parts at the macro and micro-level, some reasoning was necessary. Use of intelligent agents achieved this. Further, IK on weather and drought is so rich; it has been said to be holistic (Berkes, Mina 2009). In order to model this aspect of IK and ensure preservation of this richness, we employed the use of Fuzzy Sets (Zadeh 1965). In order to build a ***complete*** early warning system, forecasting/predicting future droughts was crucial; ***Artificial Neural Networks (ANNs)*** were used for this purpose. Finally, artificial intelligence algorithms are used in customising the syntax and semantics of the drought alerts to suit the diverse audience, hence ***generic***. In further work, the latter could be employed for handling: (1) Natural language translation aimed at supporting African local languages; and (2) Text-to-speech translation so that alerts can be read out to users who cannot read.

4.3 DEWS Framework Architecture

Putting together all the aspects discussed above resulted in our novel architecture for the integrated Drought Early Warning System that has three main components: (1) Drought Risk Knowledge; (2) Drought Monitoring and Prediction; and (3) Drought Communication and Dissemination.

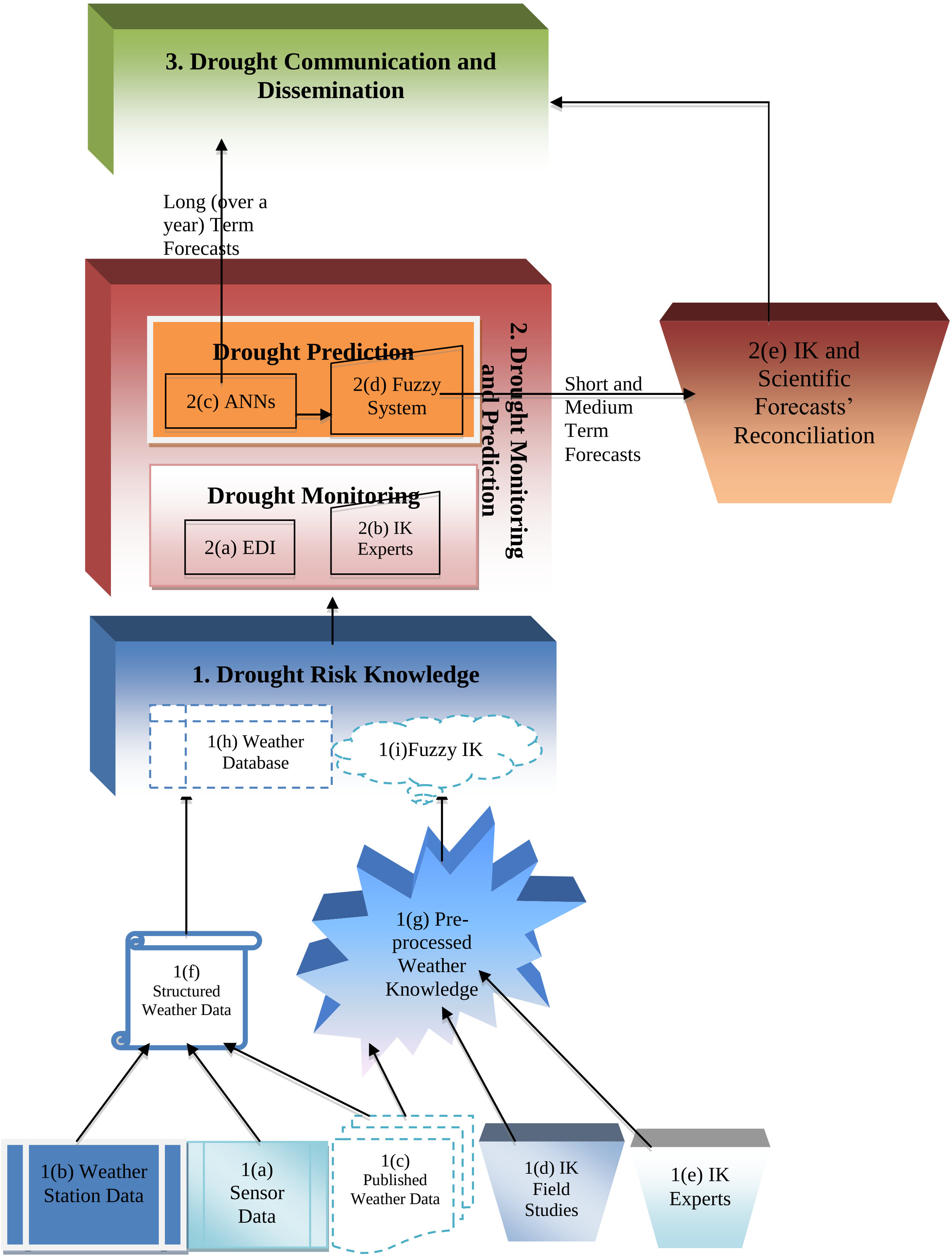


Figure 4-3: Integrated Drought Early Warning System Framework

The Framework above has the following features:

4.3.1 Element 1: Drought Risk Knowledge

1(a): Using wireless sensors that are capable of sensing temperature, humidity, atmospheric pressure, wind (direction and speed), precipitation and soil moisture, weather data is automatically collected and sent to a structured store ***1(f)*** in form of text messages (SMS). This is achieved through a GPRS module that is part of the sensor equipment that is being used for this research. Once in the store, queries are used to retrieve data in the required formats and presented to Drought Monitoring and Prediction component.

1(b): In order to achieve a complete integrated system, the data observed from manual weather stations is manually entered into the system and stored in the same database as the sensors' data.

1(c): Other data elements (IK) are retrieved from various publications available in print and on-line. Out of these, the structured elements are stored in ***1(f)*** while the unstructured ones are stored in ***1(g)***.

1(d): Prior to commencement of the system development, various field studies were carried out to establish the structure (and categorisation if any) of the IK on droughts. During this phase, various indicators were also collected and stored in 1***(g)***.

1(e): This is the 'real-time' (nearly) collection of the IK from the IK Experts. This is achieved via a mobile phone application which is designed such that each record entered is transferred to IK storage via WAP. As shown in ***Figure 4-4***, at this stage, services of an intermediary are used, he/she sieves through the discussions by the IK Experts, translates, formats and keys in the information on to a mobile phone application.

1(h) and **1(i):** the structured data is stored in a database ***1(h)*** while the pre-processed indigenous knowledge is represented as Fuzzy Sets ***1(i)***.

4.3.2 Element 2: Monitoring and Prediction

This is implemented using two sub-components: (1) Drought Monitoring and (2) Drought Prediction.

i. **Drought Monitoring**

This receives both IK and weather data in pre-defined formats. The component then pre-processes the data to detect suggestive patterns as well minimise duplicates and other errors. Once this is done, the generated indicators are presented to the Prediction Component.

2 (a): Using precipitation data, EDI and AWRI are computed to determine the drought levels.

2(b): IK experts' representatives send in real-time IK observations via mobile phone application. Through this component also, vetted/registered members of public are allowed to send in alerts of extreme events (for example flash floods) via text messages.

ii. **Drought Prediction**

This partially automates the forecasting stage using ANNs and Fuzzy Logic. **2(c)** and **2 (d):** Using ANNs that are pre-trained using past values of EDI, AWRI and Precipitation, drought forecasts for short, medium and long terms are made and the respective EDI/AWRI values generated. For further analysis, medium and short-term forecasts are passed to the IK Fuzzy system ***2(d)*** where they are integrated with IK indicators. On the other hand, since it is evident (from literature) that IK rarely takes care of the long-term (beyond a year), forecasts for this category are sent to the Drought Communication and Dissemination Component directly.

2(e): The resulting forecasts are reviewed by both the scientists and IK Experts after which 'reconciled' forecasts are generated and passed to the Dissemination component. This is partially a manual activity where the meteorologists and the IK experts sit to reconcile SCFs and IKFs. However, the short-term forecasts (a few hours to two weeks) do not need the manual 'reconciliation'; the system intelligently reconciles the two (from IK and from ANNs) and sends them to the Drought Communication and Dissemination Component. Further, in line with fuzzy system, for purses of 'recovering' IK's original meaning/format, the output 2(e) is passed through 1(i) for Defuzzification

As shown in detailed architecture (Figure 4-4), component 2(e) utilises the Global Weather patterns using standard data interchange formats for structured information such as Really Simple Syndication (RSS) and Extensible Markup Language (XML), Regional Weather Forecasts (from other Climate Zones in the country) and also the National Weather Forecasts. This integration of SCFs and IKFs is made easier by the fact that all data (the IKFs and SCFs) are represented using similar formats. Another attribute of the framework is the system's ability to 'learn'; 'New Knowledge' generated from new/subsequent forecasts is ploughed back to the Drought Monitoring and Prediction Component for use in the future. This can also be used to detect phenomena such as climate variations.

4.3.3 Element 3: Forecasts Dissemination

Our framework seeks to automate and complement the existing drought alerts/weather forecast information dissemination methods in use in SSA. Mobile phones are used to send customised forecasts in form of test message and where possible, free phone calls to the farmers. Other forecasts are posted on websites while others are generated in audio formats that can be broadcasted via community radios stations and visual displays on strategically located village digital billboards. Though not implemented, the Framework is designed to support natural language processing to allow for translation of the forecasts into the local languages.

To further expound on how components 2(e) and 3 interact, below is a more detailed architecture:

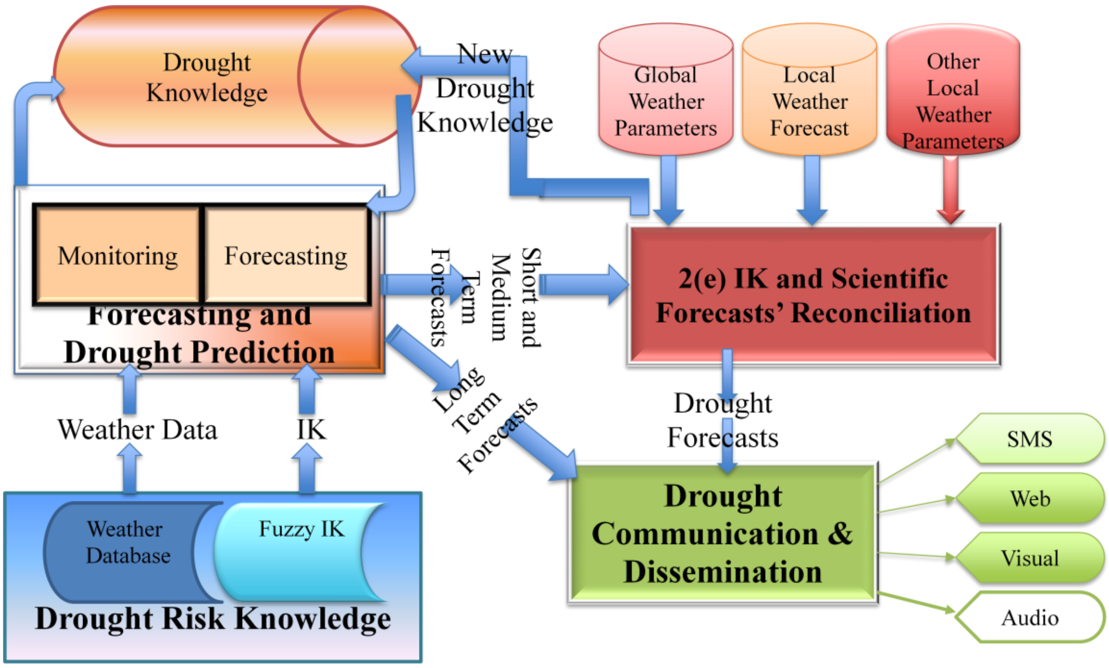


Figure 4-4: Integrated Drought Early Warning System Architecture

4.4 DEWS Framework – Role of ICTs

The critical role of ICTs in each of the three elements of our EWS framework is captured in the sub-sections below.

4.4.1 Wireless Sensor Networks

Before settling on one Libelium's (http://www.libelium.com) agriculture board, the authors reviewed a number of weather sensor boards using factors such as openness (software and hardware), cost, deployment readiness, programming API and support for relevant (to weather and climate) sensors. The latter is critical for this work given that the minimum meteorological parameters needed for weather-related decision making are (Plummer, Terry et al. 2010); (1) precipitation (type and amount); (2) surface air temperature; (3) atmospheric pressure; (4) Wind direction and speed; (5) relative humidity; most sensor boards reviewed were found to lack support for (1) and (4).

4.4.2 Service-Oriented Computing on Mobile Phone Grid

Low Internet coverage and lack of electricity in the rural areas of most countries in SSA will affect the deployment of the computer-based DEWS. Luckily, most of these countries have reported impressive adoption levels of mobile phones (ITU 2010b), a phenomenon that has created a paradigm shift where computing is slowly moving from the traditional PC to the phone. Coincidentally, advancements in the Smartphone technology have produced such powerful gadgets that can ably compete with PCs of the 21st century. Today (2012), for about US$ 100, one can acquire a Huawei Ideos (Android) phone in Kenya equipped with; 528MHz clock speed, 256MB RAM with support for 16 GM MicroSD, several data links (Bluetooth, wifi, 3G, EDGE), Wireless local-area network (WLAN) among other features (www.safaricom.co.ke). With this kind of computing power, some aspects of the DEWS can be developed to run on these mobile phones, hence, making the system affordable, sustainable and resilient.

However, given the following inherent characteristics of mobile phones, building DEWS that runs on mobile phones is indeed a daunting task that requires innovative approaches.

i. Mobile phones are personal possessions and are almost always in the possession of their owners. This makes getting physical access to the phone when it is idle difficult for a third party;

ii. Mobile phones are, by definition, mobile, even with some way to tap into the computing power of the phone, one must contend with the fact that this power will not always be physically located where it's required;

iii. Mobile phones vary in terms of their design and capabilities. While one device may be well suited for one task, another may be better suited for another. The capabilities of these phones may also not be compatible;

iv. Most mobile phones, especially in African countries, are low end and may be limited in terms of their processing power and the applications they can run;

v. Mobile phones rely on batteries for power. These batteries drain very fast especially under heavy load. Any attempt to utilise idle time would result in the battery draining even faster.

In the case of this research, the possibilities of using service oriented computing on a mobile phone grid were investigated under the following prototypes:

a) MobiGrid

MobiGrid (Masinde, Bagula et al. 2010) is a middleware for mobile phones that provides a generic API on which mobile applications can be implemented to use resources of several mobile phones within a grid. For the purposes of this research, MobiGrid was designed to mitigate some of the challenges of mobile phones described above. It was designed around the following functional requirements:

i. As a system to establish communication between the various nodes, complete with a messaging system with a finite set of commands understood by the nodes;

ii. A way of determining which nodes are in the grid and what services they offer;

iii. A way to determine a coordinator as well as an election system to manage the transparent election of new coordinators in case of failure;

iv. A facility for service discovery, capable of monitoring all active and failed nodes to determine which services are still available;

v. Ability to recover from faulty communication.

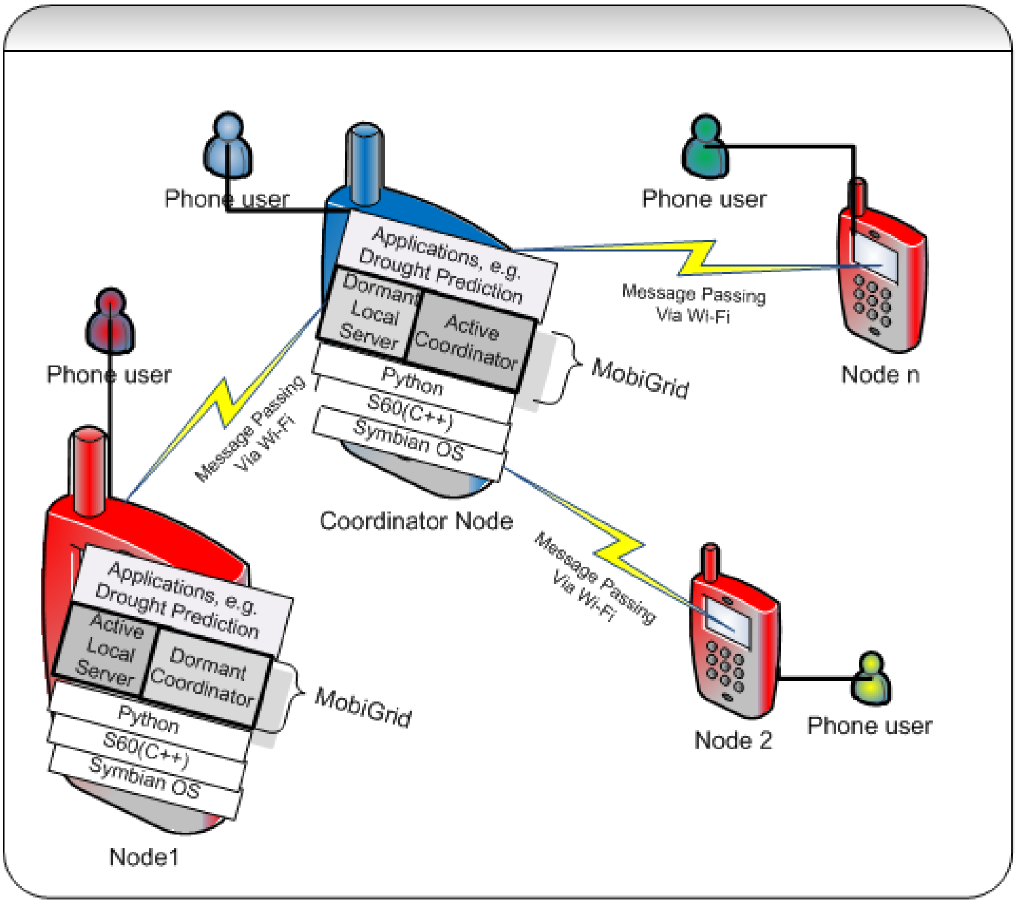


Figure 4-5: MobiGrid Architecture

b) MobiSOC

With MobiGrid in place, SOC (Masinde, Zebal et al. 2012) was then used to implement localised computation of the Effective Drought Index. Real-time weather data from the wireless sensors is used to compute the drought index for the local area where the sensors are installed. All this is achieved on mobile phones as shown in the architecture below.

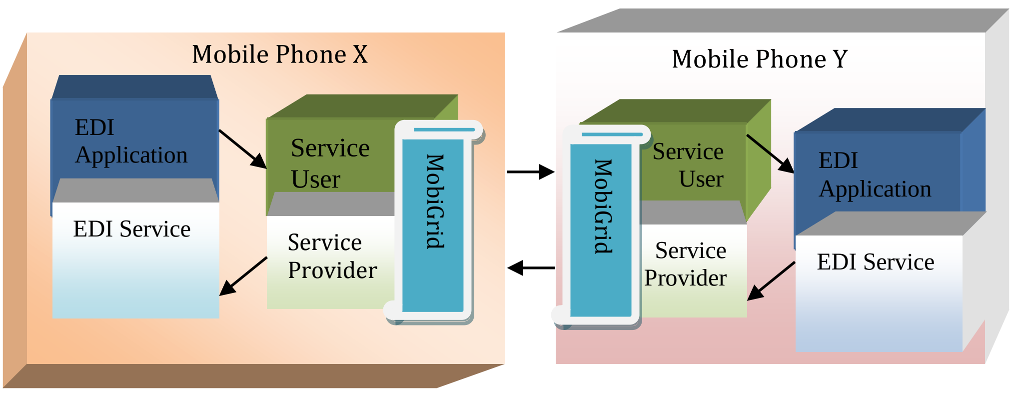


Figure 4-6: MobiSoc Architecture

4.4.3 Web Service, RSS and XML

At the various points in the architecture, web services, Really Simple Syndication (RSS) and Extensible Markup Language (XML) universal data interchange formats are adopted. The advantage of this approach is that, it becomes easier to incorporate information and data to and from other external sources such as the internet.

5. Collecting Drought Risk Knowledge

'Collecting Drought Risk Knowledge' is the systematic collection of data on droughts and assessment of drought risk

''Not everything that counts can be counted, and not everything that can be counted, counts'' [Albert Einstein]

Sometimes the more measurable drives out the most important. [René Dubos]

5.0 Introduction

Having set out the blue-print for implementing an Integrated Drought Early Warning System in Chapter 4, this chapter starts off the implementation of this framework by tackling Component 1: Drought Risk Knowledge. This is build from two sources: indigenous knowledge and structured weather data from sensor-based weather meters and conventional weather stations.

From the discussion on IK presented in Chapter 2, it emerges that indigenous drought forecasting indicators in the tropics can be categorised under: (1) Patterns of seasons (cold, dry, hot, rainy, etc.); for example nature and date of rainy season onset; (2) Animal, insects and bird's behaviour; (3) Astronomical; (4) Meteorological; (5) Religious beliefs, prophecies, myths and cultural practices; (6) Human nature and behaviour; (7) Behaviour of plants/trees, for example fruit and flower production. It is also true the ranking of these indicators by the various communities depends on their socio-economic factors and general way of life. People from the same community observe different parameters depending on their day-to-day occupation; herders will observe birds' nests as they graze the cattle, women will observe water bodies (rivers and wells) as they fetch water and so on. Finally, these indicators overlap and they mostly depend on each other; their interpretation cannot therefore be done in isolation of each other. If/when subjected to scientific rigor, most aspects of IK on drought forecasting do not belong to clearly defined nor mutually exclusive categories; this is analogous to fuzzy sets. Further, the consequences/implications of indicators are always detailed pieces of information advising the local people on various courses of action.

In the current work, the sparse network of weather station is complimented through the adoption of the more cost effective (than conventional weather stations) wireless sensor-based weather meters. The sensor boards used supply fairly structured weather data for 7 parameters: (1) temperature, (2) relative humidity; (3) atmospheric pressure; (4) precipitation; (5) soil moisture; (6) wind speed; and (7) wind direction. The sensor boards are equipped with GPRS and GPS capabilities among others and are therefore able to automatically send the sensor readings to a database via SMS-gateway. Since the sensor-boards are meant to complement (not replace) the conventional weather stations (where available), the implementation of this data source component includes a user-interface through which weather readings from the latter are entered into the database.

5.1 Data source 1: Indigenous Knowledge

In this section, IK data from the Abanyole and Mbeere communities in Kenya was used to determine the overall design of the IK data collection, storage, manipulation, and to some extent, the dissemination sub-system. The data was collected within a related project (Masinde, Bagula et al. 2012b) carried out by the authors.

5.2 Mbeere and Bunyore Community Case Study

(a) About the Mbeere Community

The Mbeere people occupy the former Mbeere District, which is now part of the current Embu County in Kenya. With a population of 168,000, the Mbeeres are the majority in the region (former Mbeere District), which has a population of about 220,000 (Kenya National Bureau of Statistics 2009). Mbeere is about 2,093 km^2 and it is located in Eastern side of Kenya. It lies between Latitudes 0^o 20’ and 0^{o}50’ South and Longitude 37^0 16’ and 37^0 56’ East.

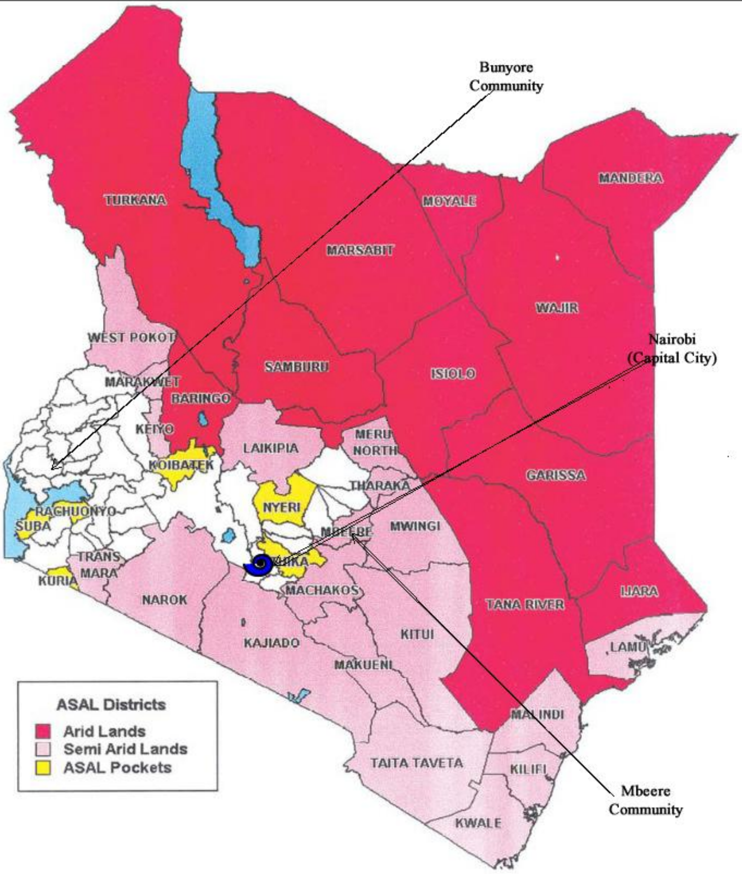


Figure 5-1: Kenya's ASALs Districts

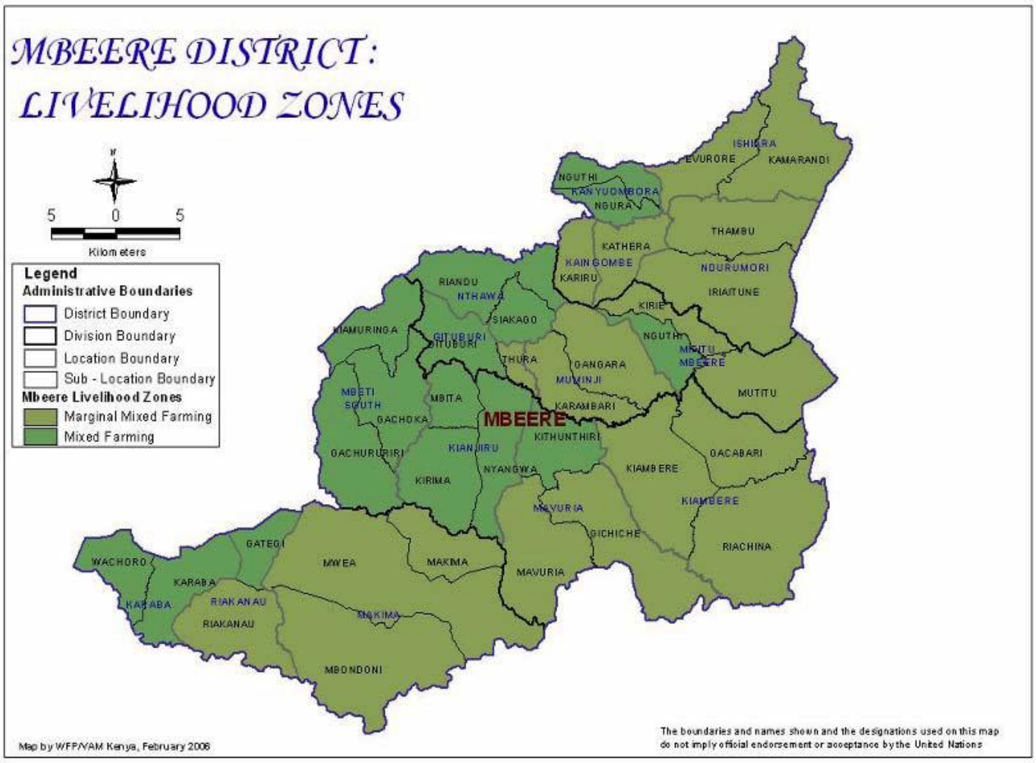


Figure 5-2: Mbeere's Livelihood Zones

Source (Republic of Kenya, 2009)

With an average of 750mm (most parts receive less than 550 mm) annual rainfall, Mbeere is classified under Arid and Semi-Arid Lands (ASALs). A further classification of the ASALs places Mbeere under Category C; 50-85% of the land is arid (Republic of Kenya, 2008), Its terrain is characterised by scattered outcropping hills and its extensive altitudinal range of the area influences the temperature, which ranges from 15^{o}c to 30^{o}c. The main source (over 80%) of livelihood is rain-fed marginal farming and livestock (agro-pastoralists) keeping. This being the case, the farmers here rely mostly on the knowledge of seasons in making cropping decisions. Like most parts of Kenya, there are two main rain seasons experienced in Mbeere; the March-April-May (MAM) long rains and the October-November-December (OND) short rains. Crops grown include maize, sorghum, millet, beans, cowpeas, green grams, pigeon peas, cotton and tobacco on farms of average of 3.5 Ha. Livestock kept include Cattle (Zebu mostly), goats, sheep, poultry, donkeys and bees (http://www2.kilimo.go.ke). Mbeere's Prevalence of Rural Food Poverty is estimated at 57.4% while Rural Poverty gap and absolute poverty are estimated at 26% and 63% respectively (CBS, 2001). Like other regions that are classified under ASALS, Mbeere has fragile ecosystems, unfavourable climate, poor infrastructure and historical marginalisation and the perennial natural disasters here are droughts.

(b) About the Abanyole Community

Bunyore is located approximately between 0.083 latitude and 34.617 longitude. The area has a population of about 162,000 (Kenya National Bureau of Statistics 2009); occupying an area of 173km^2. Unlike Mbeere, Bunyore has an equatorial climate with evenly distributed rainfall ranging between 1750mm and 2000mm (http://www.meteo.go.ke); MAM and OND are the main rains seasons here too. Abanyole (*Ava-Nyole*) are one of the 16 sub-tribes that form the larger Luhya community; the earlier is found in the larger Kakamega County.

Of significance to this research is the *Nganyi family* which is a sub-clan of the larger *Abasiekwe Clan* of Bunyore. The family is well known for having produced rainmakers for tens of years; they utilize their rich IK on weather and their environment to offer forecasting services to the people of Bunyore and beyond. The critical contribution to this sensitive topic of climate has been recognised by several organisations including the Kenya Meteorological Department (KMD) which initiated an integration weather forecasting project between the Department and the Nganyis

(Ziervogel, Opere 2010). This initiative has gone a long way in downscaling weather forecasts to the local level and as can be seen below, courtesy of this project, the Abanyoles are more informed about SCFs than the Mbeeres.

(c) Sample Data and Sampling Phases

The data used in this research was collected in 2 phases:

i. **Phase I:**

This took place between August and December 2010 and the aim was to identify the prevalent IK indicators used by the Abanyole and Mbeere people. A guided interview involving 95 (55 from Abanyole and 40 from Mbeere) respondents was carried out with the help of representatives from the two communities. The interviews sought to find out the following pieces of information:

- Respondent's background information such as bio-data. Of importance to IK were the details of respondents' migration history because the latter influences one's exposure and understanding of IK;
- Drought and weather prediction section sought to find out details such as the local name for droughts, who predicted (if at all) droughts in the community and knowledge of any historical droughts. The section also sought to find out the various IK indicators that the community used to forecast events such as rain onset, dry/wet spells during the rainy season and rain cessation. Issues of how they arrived at various cropping decisions were also discussed. The IK indicators listed by the respondents were summarized and after discussions with the groups, the most representative ones were used in the design of an IK sub-system;
- Awareness and satisfaction of the forecasting and warning services offered by the KMD;
- Respondents' mobile phone ownership (and phone model) and/usage; this was aimed at evaluating the feasibility of using the phones for droughts/weather forecast input/output.

ii. **Phase II**

This was carried out between June and July 2012 and the objective was to evaluate the usability and relevance of the integrated drought monitoring system. Like in Phase I, guided interviews were conducted and the same (as for Phase I) respondents were approached. During this survey, sample output from the integrated system (output from the mobile application) was demonstrated to the respondents for feedback. The analysis of this survey is included in the Evaluation Chapter.

(d) Weather Observations Equipment

Bunyore area is served by the Kamamega synoptic station which is over 20kms away. However, it is in the KMD's strategic plan to install an Automatic Weather Station within Bunyore (http://www.meteo.go.ke). The current sparse coverage by the weather stations may partly explain why despite the overwhelming knowledge and access to KMD forecasting services, the Abanyoles rank the services as poor.

On the other hand, there is no synoptic station in Mbeere; the nearest is over 20 kilometres away; past Embu town. The location of this station does not do justice in reporting the weather for the entire Embu; it is located in a climatic zone whose soil moisture and temperatures are conducive for tea growing. Consequently, the weather forecasts issued for Embu have no relevance (most of the times) to the lower part of Embu County where Mbeere is located. This explains why over 90% of the respondents gave a value of between 0 and 1 (out of 3) for both accuracy and relevance of weather forecasts issued by KMD. Further, the few respondents that were aware of the alert service could only give examples of such events happening elsewhere in the Country but none in Mbeere.

(e) Phase I – Data Analysis

i. **Respondents' Geographical Distribution**

In the case of Mbeere, the respondents in both surveys were drawn from several villages as shown in the figure below:

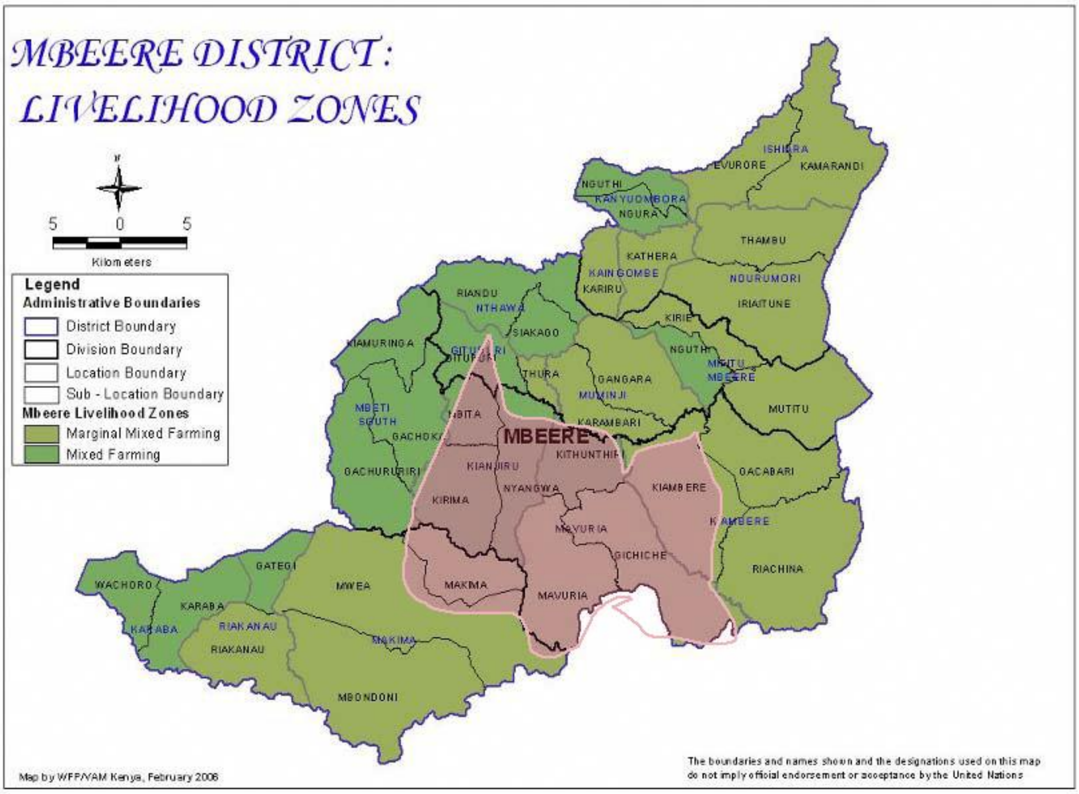


Figure 5-3: Geographical Distribution of the Mbeere Respondents

For the Bunyore case study, the smaller (than Mbeere) geographical area enabled coverage of over 80% of the region. There were 44 respondents from Mbeere and 55 from Bunyore; 2 of the respondents (both under 18 in age) from Bunyore were omitted from the analysis because they were too young to made independent decisions.

ii. **Knowledge and SFCs**

In the interview, the respondents' knowledge of KMD and the services the Department offers was sort. Those that knew about the services were asked to rank them based on *accuracy*, *clarity*, and *relevance*. However, it was noted that most respondents from Mbeere and a few from Bunyore knew about the services but did not link it to KMD. The final part asked the respondents to name the channels of communication that they used to acquire this information; the options given were *radio*, *TV*, *Internet*, *newspapers* and *others*. Those that gave more than one source were asked to give the preferred source; radio was both the most commonly used option and also the most preferred.

The type of services offered by KMD was classified under '*Forecasting'* and '*Warning*. Respondents' knowledge of both services (Forecasting and Warning) was sort and while less than 10% of the respondents knew about the warning service in Mbeere, over 50% of respondents from Bunyore knew about it and easily gave relevant examples.

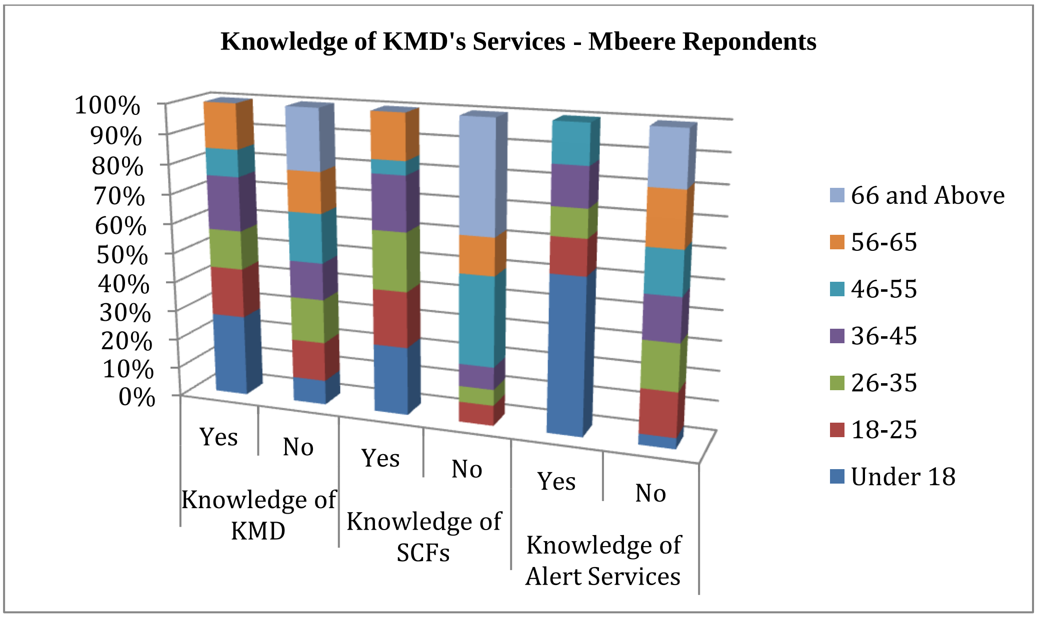


Figure 5-4: Knowledge of KMD's Services - Mbeere Respondents

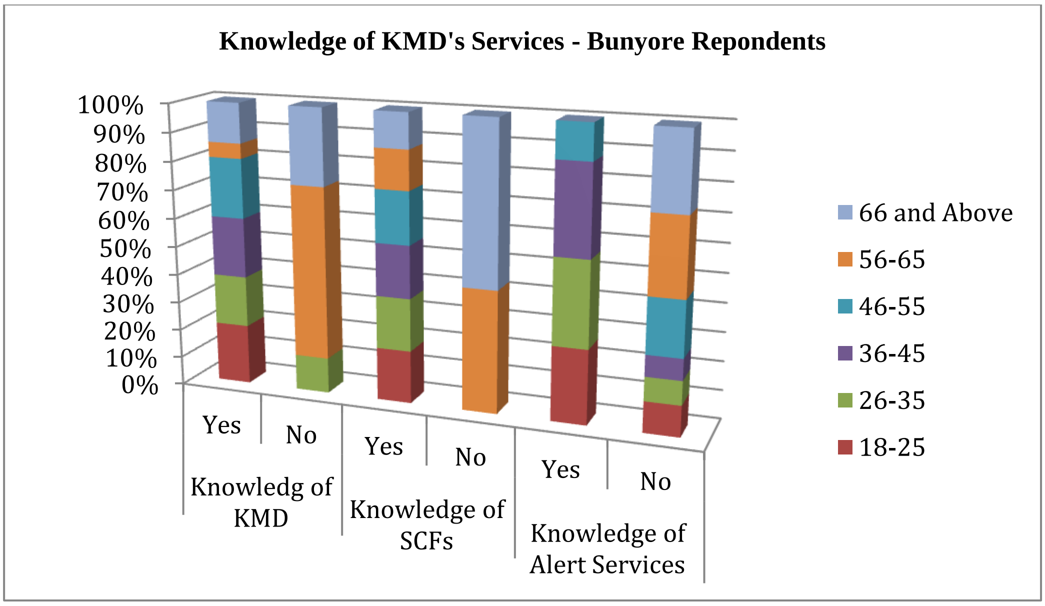


Figure 5-5: Knowledge of KMD's Services - Bunyore Respondents

iii. **Respondents Distribution by Gender and Level of Education**

By Gender, 75% of the Mbeere respondents were female and 49% for Bunyore. When it came to level of education, the lead community representative had an influence in the choice of respondents. In Bunyore, the lead person is a female professional nurse (in the 36 and 45 age bracket); the Mbeere case study was led by a young (in the 18 and 25 age bracket), jobless lady who had just completed high school. This may explain why many of the Bunyore respondents possessed post-secondary education qualification and had some formal jobs. On the other hand, the Mbeere lead person approached mostly semi-literate small-scale/peasant agro-livestock female farmers.

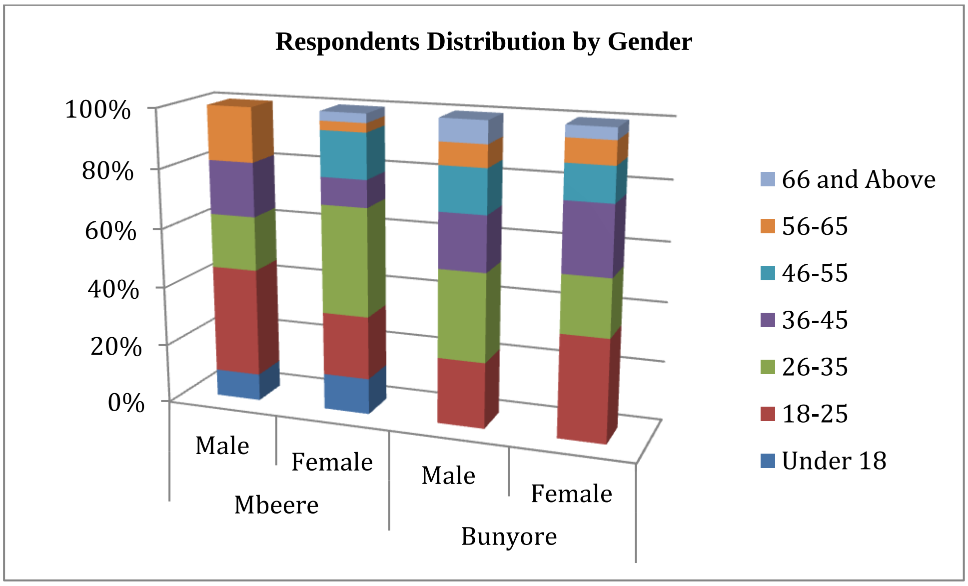


Figure 5-6: Respondents Distribution by Gender

In the Mbeere case study, there were way more literate men than women; the Bunyore case was more of a 50-50. In both cases, the number of illiterate people dropped with decrease in age and all young people had some basic literacy level. In the two charts below, *Level0* is for no formal education at all; *Level1* – Primary Level, *Level2* – Secondary Level and *Level3* – Post Secondary Level.

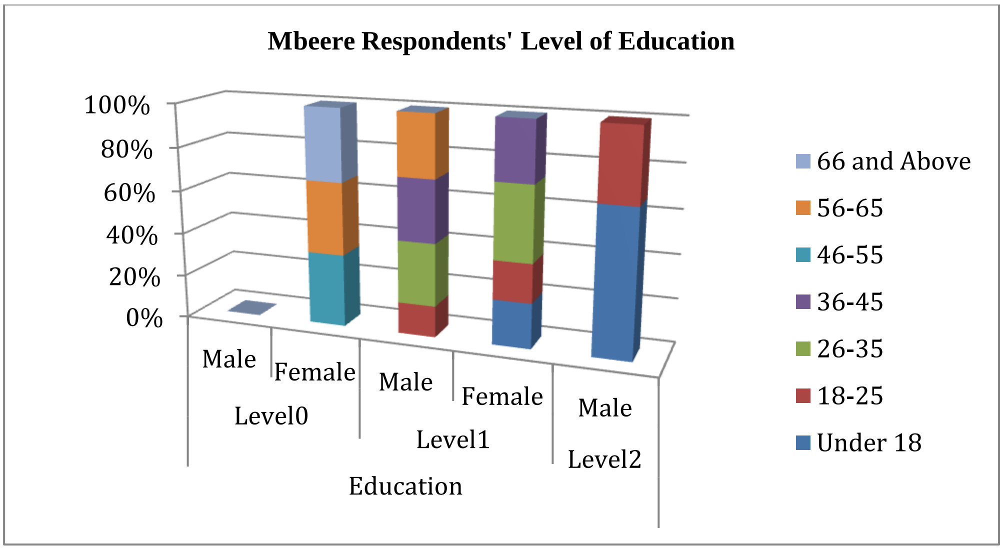


Figure 5-7: Level of Education for Mbeere Respondents

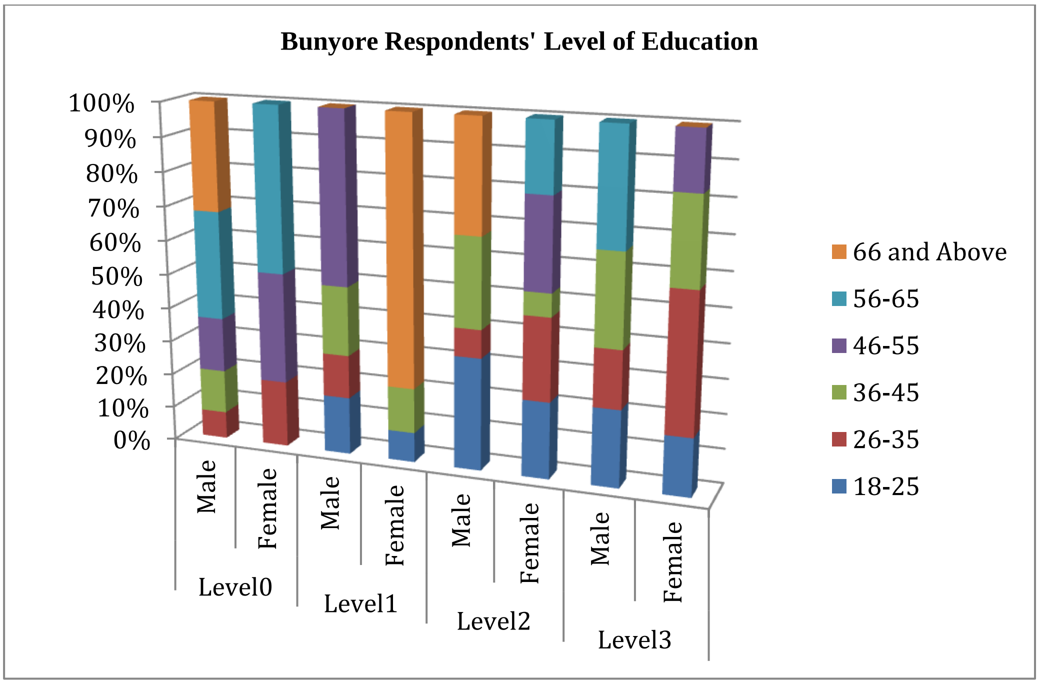


Figure 5-8: Level of Education for Bunyore Respondents

iv. **Mobile Phone Ownership and Usage**

There are generally more men that own phones than women, hoewever, all (except one) the people that did not have a phone did use phones mostly from relatives. The phones were used mostly for social calls and for mobile money services. A trend where the younger and educated correlated with phone owneship was also observed. This explains why 72% of the Bunyore respondents (were more education) owned phones cmpared to 52% of the Mbeere respondents. Information on the respondents type (smart or low-end) of phones the respondents onwed was also collected. It turned out that all the phones owned by the Mbeere respondes were low-end and only 2 phones (5%) of those owned by the Bunyore respondents were smart phones. This further informed the decision to design the system around an intermediary to whom a smart phone was supplied.

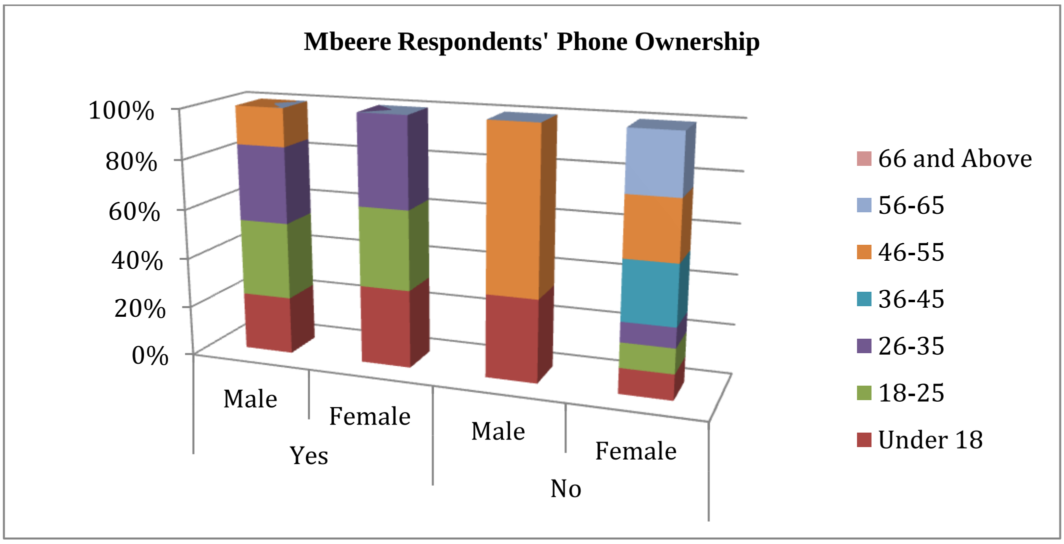


Figure 5-9: Phone Ownership among Mbeere Respondents

v. Phones for Weather Forecasts' Dissemination

As shown in the table below, the lack of relevant weather information among the Mbeere respondents may have motivated their willingness to receive forecasts over the mobile phone. Their counterparts in Bunyore were not as eager as demonstrated by the lower response (72% vs. 89%) for Yes value. The Bunyore respondents also seemed more informed and some would be heard posing the question: "*who will pay for all these text messages*" and "*who will educate the people on the details of these text messages*?" More than 40% of the Bunyore respondents recommended that weather experts be sent to the grassroots to educate the people more.

Table 5-1: Interest in using Mobile Phones for Forecasts

	Yes	Not Sure	No
Mbeere	89%	2%	9%
Bunyore	72%	13%	15%

vi. Text Messages, Via Authority and in Local Language

In both communities, despite the huge number of people willing to receive forecasts over the phones, more than 50% of these preferred that such forecasts are sent to them via an authority such as Chiefs and Village Elders. Over 80% of respondents recommended that the forecast be in the respective local language and if phones are used the literate ones preferred text messages while the illiterate chose phone calls.

vii. **IK Indicators**

In order to collect informative IK indicators, the survey was structured into two sections; IK indicators associated with various seasons and specific indicators that the people looked out for before making major cropping decisions such as to/not and what/how to plant/harvest. Like in most other communities/regions, the indigenous weather/drought indicators among the Mbeere and Bunyore people are associated with seasons. The diversity, level of details and systematic nature of the indicators from the respondents confirmed that the two communities have very rich IK systems that help the people cope with and adapt to the environment; for example, mixed agriculture.

Livestock keeping and crop farming complement each other; the animal waste is used as manure and the crops remains (especially maize stock) are preserved in dry places and used as fodder for the livestock during the dry months. In Mbeere for example, in late February, late July, August and September, the animals are left to graze freely in the farms. Another complementary role is that the Mbeere people mostly (over 90%) employ the use of oxen to prepare the farms for planting.

The Mbeere people refer to the MAM rains as *mbura ya nthoroko* (the rains of cowpeas*)* and the OND rains as *mbura ya mwere* (the rains of millet). Cowpeas (and indeed other crops like beans, green grams and maize) require more moisture than millet (and others like cassava and sorghum). Over the years, the community has accumulated this knowledge and use it to make decisions on what crops to plant in each of the seasons. Some respondents however expressed the frustrations due the erratic weather patterns; for instance, the MAM rains no longer sustain the maturity of beans and cowpeas and they have resulted in planting some of the crops meant for the short rains especially millet.

The awareness of IK indicators for weather is more widely spread among the Abanyoles than the Mbeeres. While this awareness seemed to diminish among the younger people in Mbeere, the knowledge was evenly distributed among the Abanyoles. The interview guide categorised the respondents under the age brackets: (1)66 and above; (2)56-65; (3)46-55; (3)36-45; (4)26-35; (5)18-25; and (6)below 18.

In particular, the role played by the Nganyi Clan featured as one of the sources of weather forecast information for the Abanyoles. Most indicators seemed to be similar with slight differences in interpretations. Most respondents talked about the strong winds (the direction for both communities differed), dark clouds, clear skies, rise in temperatures about 24 hours before rains, hyper-activity among bulls, presence of flogs, flowering/leaving (and shedding of the leaves)/fruiting of some trees and movement/behaviour of birds and insects. The IK relating to human behaviour and spiritual beliefs differed a lot; the knowledge was more common among the Abanyoles than the Mbeere.

The IK indicators come in handy when the people are making decisions on when to start and stop planting. There are situations where farmers have planted crops too early and headed up incurring heavy losses; many respondents in Mbeere gave the example of the 2011 MAM that did not start until late April (instead of mid March). Other respondents gave examples where some farmers experienced bumper harvest just because they planted earlier than others; their crops took advantage of the shorter rains to grow to critical levels while those planted later withered before yielding. The indicators are also used to control the supply-demand chain; for instance, the Mbeere people share the belief (out of historical patterns) that an extremely good harvest is always followed by two seasons of meagre harvest. For this reason, many farmers in this community resist the temptation of selling off their produce just after harvest because they end up purchasing same produce at much higher prices.

viii. IK Indicators, Occupation and Gender

Since observation of indicators is associated with the daily contact with the environment, women easily listed more indicators than men. In both communities, women mostly till the land and they go to fetch water, hence they are able to notice many indicators. Young men whose main occupation is attending to the animals also listed more indicators related to animal behaviour than their counterparts.

ix. Biodiversity Degradation and IK Indicators

Respondents expressed concerns that some IK indicators are no longer easy to notice because of biodiversity degradation. Respondents of *Mumburi* Village in Mbeere for example used a watering point called *Cavari* (translates to ‘marshy area’) to determining rains cessation. When the wells reached a particular level in the month of September; then rains would be falling in less than a month. Similar concerns were raised by the respondents of *Rugogwe* Village who used wells-level dug along the U*uya* seasonal river to predict rains onset. The indicator related to nesting levels of the *ngoco* bird was also difficult to observe because trees (along the water bodies especially rivers) on which the nests were observed had since been cut down. Studies carried out among the Banyales (in relation to Nganyi Clan) such as the one by Ziervogel, Opere(2010) also revealed that the strength and relevance of a number of IK indicators have been eroded by biodiversity degradation.

x. **IK Weather Indicators for Mbeere People**

IK among the Abanyoles has extensively been studied under the Integration Project by Ziervogel, Opere (2010) and was not therefore pursued further in this research. Consequently, the remainder of this section pays more attention to the IK indicators for the Mbeere people. However, a few of the indicators from the Abanyoles were used for the purposes of demonstrating the functionality of the integrated DEWS.

In the Mbeere case, it was noted that there are more indicators associated with the OND rains than the MAM ones. As it were, the interval between the OND and MAM rains is short and most respondents indicated that the patterns observed during the OND give some indication of the nature of the MAM rains.

Table 5-2: Mbeere IK Weather Indicators

	January - February	Long Rains (*mbura ya nthoroko*)	Dry Season (June to September)		Short Rains (mbura ya mwere)
			Cold Part (*mbevo*)	Hot and Dry (*Thano*)	
Seasons' Onset, intensity and duration	• This period forms the transition from OND and MAM rain seasons. In a normal season, the OND rains end in the second week of December and the MAM starts in the second week of March;	• Starts by second week of March and ends in the first or second week of June • Late onset and/or early cessation is sign of a bad season • Crops requiring more moisture are planted	• Extremely cold and foggy (nundu) • Starts from the second week of June and Ends in the last week of July or first week of August	• Starting from the last week of July or first week of August to the second week of October	• Early on-set (second week of October) is a sign of a good season; late on set is sign of a bad season • The onset is accompanied by sharp lightening that is spotted from the East

	January - February	Long Rains	Dry Season (June to September)		Short Rains (mbura ya mwere)
			Cold Part (*mbevo*)	Hot and Dry (*Thano*)	
Meteorological	• Moderate temperatures (less than 25^0C) is considered good; it ensures that the annual crops (cotton and pigeon peas) survive until the MAM rains	• Presence of thunderstorms and lightening is a sign of good season • Intense heavy showers mostly falling in the evenings and early parts of night is a good sign • Very warm nights is a sign of rains within 24 hours	• Night temperatures to 15^0C or below • Intense cold implies abundant rainfall in the rainy season • The cold sometimes accompanied by drizzles retains the moisture from the MAM rains and gives late (planted) crops a chance to grow. Late (and annual) maturing crops such as pigeon peas also benefit from the cool temperature and so are animals because the water bodies retain water for longer and the fodder does not wither fast. • Cowpeas plants grow new leaves that are used as vegetables • Interruptions of the cold season by days of warm temperature implies drought spells during the rainy season • Strong and destructive winds are a bad omen at this time; they carry away stocks (of crops) that are used as fodder for animals	• Intense hot temperature predict abundant rainfall; the community belief that the temperatures '*cook'* the rain. • East-West very Strong whirling (*kïthirü*) winds observed in the September is a sign of favourable season. There are many water bodies on the East; translated to mean that the wind is carrying the water to go 'make' the rains • Very warm nights is a sign of rains within 24 hours	• Presence of intense thunderstorm with no rains is sign of a bad season • Moderate start (not storms) is a good sign • Rains falling mostly during the day (from 11 am onwards) is a sign of a good season • Storms and hailstones are considered bad omen; they bring down millet stocks which are generally weaker than maize • Dew in the morning is a sign of dry spell onset.

	January - February	Long Rains	Dry Season (June to September)		Short Rains
			Cold Part (*mbevo*)	Hot and Dry (*Thano*)	
Flower, leave and Fruit Producti on	• Good yields by mango trees that produce large fruits (e.g. *ndoto*) is good sign, the vice versa indicates a poor season • Good yield from some wild fruits such as ngaa is a bad sign.	• Germination of nthinuriu is a sign of good season • Flourishing of edible wild tubers (*mbaku*) and some wild fruits such as *ngawa* and *Njiara* is a sign of poor season; the fruits are seen as God's provision in place of food	• Producton of secondary leaves by cowpeas is a good sign (there is still moisture in the soil) • Very leafy *migaa* is good sign; the trees branches are usually cut and used as fodder for goats and sheep	• Maturity of the wild fruits of the *Mutiru* (ndiru) is a sign that the OND rains will be stating in less than 2 weeks' time • Flowering of *muramba* (oak tree) is a sign of rains onset • Germination of *karamba ka nthi* is a sign of rains onset • Flowering of *mugaa*, *mutororo*, *mukuu* and *muthigira* means rain are 2 weeks away this is true when there is shedding of seeds my *muthuri* and *gakega*	• Flowering and fruiting of drought-category mango trees is a sign of bad season • Flowering and fruiting of large category mango trees is a sign of good season

	January - February	Long Rains	Hot and Dry (*Thano*)	Short Rains
Birds		• Sounds from a bird called *kivuta mbura* (means rain puller) is a sign of good harvest	• Low nesting by the *ngoco* bird along water bodies is a sign that rains will be poor and favourable vice versa	• Flocks of the *thari* bird seen migrating from west to Mbeere is a bad sign. The bird's name means 'snatch' (*ku-thara*) and it is interpreted that the birds are coming to snatch the little meagre crop (millet and sorghum) from the farmers • When *thari* birds result to invading the maize crop, an extreme drought is predicted
Animals	• Very many goats give birth is a good sign; the sign is stronger when twins are born	• When young bulls jump and down as they return home, it is a sign that rains will fall in less than 2 weeks • Presence of overly many baboons is a sign of a poor season. The rains are not adequate to support their wild sources of food and water	• When cows unwilling leave (they are forced) to leave the water points is a sign of poor OND rains	• A good season is predicted if the libido among the animals is high. • Hopelessness expressed by bulls that refuse to plough (and lie down instead) is a sign of poor season; it is interpreted that the bulls are telling the farmers that they are wasting time planting and yet the crops will not mature

	January - February	Long Rains	Hot and Dry (*Thano*)	Short Rains
Insects	• If movement of *midithu* as if they are kissing the ground is noticed in late February, then the rains are less than a month away.	• If after about two weeks of rains frogs are heard croaking in nearby water bodies, then the harvest will be good • If beetles are seen pushing huge balls of cow dung (or human waste), the season will be good. The beetles are said to be preparing homes for their offspring • If *Bugvare* are observed filling their nests to the brim with dirt after about 2 weeks of rains, it signify good season – same as full granary • Presence of white frogs on grass is a bad sign. These frogs are known to kill cows if they (cows) ingest them in the course of grazing	• *Mindithu* starts moving southwards	• Noise from *ngiri* in the early evening is a sign of onset of a dry season. Farmers still planting should be alarmed because their seeds may not germinate
Astronomical		• Rain onset is predicted to be around the time of the a new moon • Visible phases of full moon signifies drier period • Dark phases of moon indicate wet period		• Rain onset is predicted to be around the time of the a new moon • Visible phases of full moon signifies drier period • Dark phases of moon indicate wet period
Spiritual Beliefs and Human behaviour	• A poor MAM season was predicted if many farmers sold most of their produce from OND season at miserable prices; this was a 'punishment from God'	• When the older people experience congested chests in early March; this means that rains are less than a week away. Scientifically, this is related to increased humidity in the atmosphere	• When a particular old man (he has since passed away) in *Kamutuanjiru* drank water for the first time in early October, (ordinarily, he did not take water at all), farmers rushed to plant because hte rains would fall in less than a week	

Source: (Masinde, Bagula et al. 2012b)

5.3 IK Data Source– Design Factors

5.3.1 Factors Description

From the analysis above, the following factors emerged as critical and were therefore pursued in designing our DEWS.

Mobile phones prevalence: there was over 98% access and/or ownership of mobile phones; those who did not own phones, had access to either relatives' or neighbours' phones free of charge. Further, 89% and 72% of Mbeere and Abanyole respondents respectively expressed the interest in receiving forecast information via mobile phone. Interestingly, when asked to give the greatest contributor to the cost of running their mobile phones, over 60% named charging the battery. This is because there is no electricity in most of the regions where the respondents lived and they had to travel far to have the phones charged at a fee. Secondly, more than 90% of the phones the respondents owned were low-end type

Text Message prevalence: - asked to choose from SMS, IVR and phone calls, over 80% of respondents chose SMS as the preferred form of mobile phone weather dissemination.

Forecasts in local language: in an open-ended question asking the respondents to suggest ways of improving the weather forecasts, an overwhelming percentage of the respondents mentioned their use of local language for communicating the forecasts.

Forecasts through an authority: asked if they would prefer forecasts sent directly to them or via some authority/leader, over 60% (especially the semi-literate and illiterate as well as the older farmers) preferred that authorities such as area Chiefs and Village Elders be used to pass the information. This was also driven by lack of confidence in interpreting IK at individual levels. This was confirmed by the answers respondents gave when asked if they reached cropping decisions as individuals or they consulted others; most of them chose the latter

Localisation: the biggest discontent with the KMDs SFCs was the fact that the information was not localised; it did not tell the people about their villages and their environment. Majority expressed the wish that the forecasts were more localised to their situation. Three respondents from Bunyore mentioned installation of more weather stations as a way of improving the forecasts.

Radio forecasts: this was the most preferred medium of weather dissemination; over 90% of respondents listened to radios that broadcasted in their local language.

Some three respondents even suggested that critical alerts should be passed to the local people through loud-speakers mounted on moving vehicles; the same way they did for political rallies. They also expressed confidence that if more regular, accurate and relevant weather forecasts and alerts were broadcasted via these local radio stations, the information would reach more people in the communities.

Integrated Forecast: the respondents acknowledged the critical role of the weather forecasts experts and the scientific forecasts issued by KMD; if only they were improved. They also expressed the concerns that there were salient features of their IK forecasts that KMD would never tell them and opted for a hybrid system that integrates both systems. The Abanyoles already embraced this idea more than 5 years ago through the Integration Project by Ziervogel, Opere (2010).

5.3.2 Conceptual Framework

The following conceptual framework was adopted to ensure that the IK indicators used in the forecasting process represented the community as whole (as opposed to individual's views). This also took care of the requirement to pass the forecasts through some 'authority'. Further, the fact that the forecasting incorporates scientific weather observations (via the Drought Prediction Application Server), the forecasts that reach the community members (via the intermediaries) are already 'integrated'.

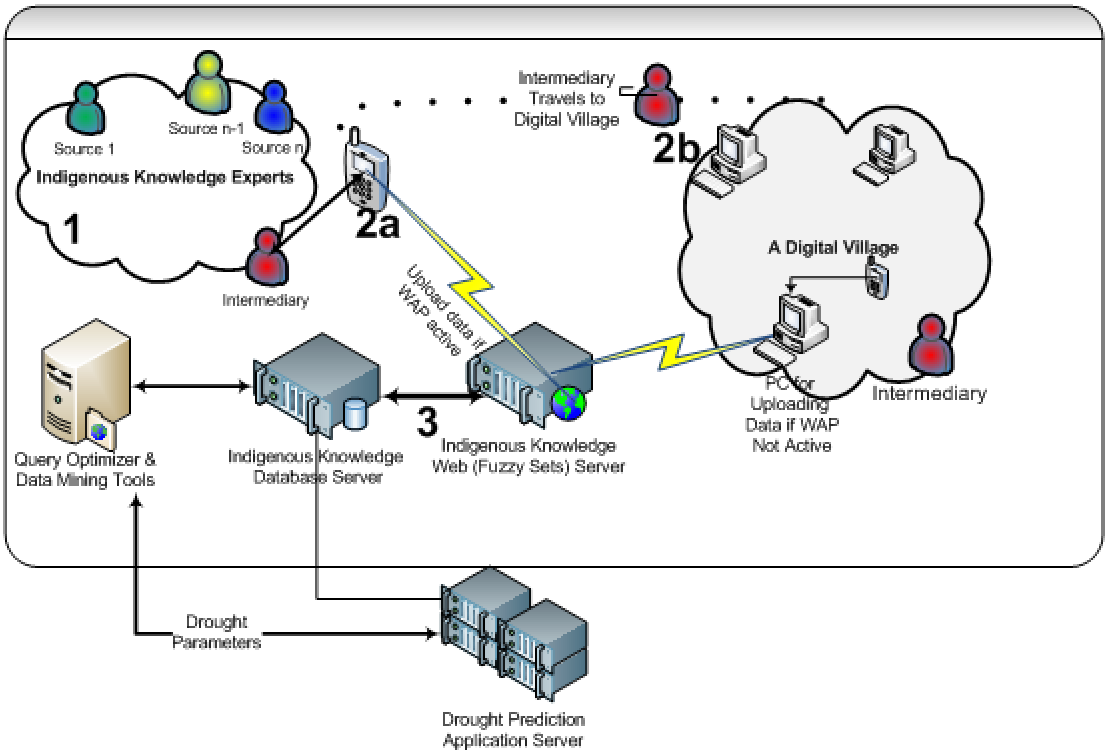


Figure 5-10: A Framework for Collecting IK on Drought

The framework above operates within focus groups setup within a given community (Mbeere in this case) and it involves the following steps:

(1) For each community, focus groups made up of people considered to be indigenous knowledge experts are formed and meet regularly to discuss various weather/climate indicators. In order to interface the information emanating from these discussions with the early warning system, an intermediaries (who understands both English and the local language as well as ICTs and meteorological terms) are identified and picked from the community.

(2a) Using a smart phone application (described later in the implementation chapter), the intermediaries key in all the IK indicators. Once the information is stored on the phone, it is sent to the Indigenous Knowledge Web Server via the phone's WAP facility.

(2b) When/if the WAP facility is not available, the intermediaries have the option of visiting the nearest Internet Kiosk[12] from where they can access the Indigenous Knowledge Web Server and upload the collected information.

[12]http://www.elearning-africa.com/eLA_Newsportal/rural-internet-kiosks-herald-last-frontier-in-bridging-digital-divide/

(3) Using various data optimisation scripts stored in the web server, the IK is stored in a semi-structured (using fuzzy sets) format in the Indigenous Knowledge Database Server.

The realisation of all the above design issues in explained in the subsequent chapters of this dissertation.

5.3.3 Fuzzy Representation of Indigenous Knowledge

To enable storage of IK and eventually its integration with the structured weather data, fuzzy logic was used; this was to ensure that the holistic nature of IK is preserved. To demonstrate this, all the IK indicators for the Mbeere community were used to design the IK – Fuzzy System. For each of the five seasons (OND, JF, MAM, JJ, AS), fuzzy inputs/outputs and the associated rankings were extracted and used in the implementation of the sub-system. These rankings reflected the importance of the indicators as listed by the respondents of the survey. Below are the input and outputs for the OND season.

Fuzzy Inputs

Table 5-3: Fuzzy IK Inputs for the OND Season in Mbeere

First Order Inputs	Second Order Inputs	Universe of Discourse	Rank
OND Rain Season Characteristics	Rain Onset	{Early; Normal; Late}	2
	Rain Direction	{South-to-North, Other-Directions}	2
	Lightening	{Sharp lightening, from East and Scattered; lightening from other directions}	1
	Meteorological Indicators	{Empty intense thunderstorm, Moderate start }, {Rains during the day; Rains other times}, {Storms and hailstones; moderate rains}, {Presence of dew in the morning; clear skies; dark clouds}	5
	Astronomical Indicators	{Dark-Moon; Visible-Moon; New Moon},	4
	Birds/Animal/Insects Behaviours	{High-Nesting-by-*ngoco*-Bird; Low-Nesting-by- *ngoco* Bird, arriving of large flocks of *thari* from west}, {Full-Nests-by-bugvare; Large-Numbers-of-Mayflies; Noises from ngiri in the early evenings}, {High libido among the animals, hopelessness by bulls pooling oxen)	5
	Duration	{Lasts-until mid-December; Longer; Shorter}	5
Fruits/Leaves/ Flowers Production	Fruit Production	{Good-Production-from-small mango variety Good-Production-from-large mango variety,}	3

(a) **Fuzzy Outputs**

Like many other communities that rely on rain for food production, the Mbeere are mostly interested in the following outputs in relation to the rainy seasons (MAM and OND).

Table 5-4: Fuzzy Outputs Inputs for the MAM and OND Seasons in Mbeere

OND Rain Season Outputs	Universe of Discourse	Weight 0-1)
Quality	{Failed-Rains, Favourable-for-drought-Crops, Favourable-for-other-Crops}	0.4
Planting-Period/Pattern	{Early, Normal, Late}	0.1
Onset	{Early, Normal, Late}	0.15
Cessation	{Early, Normal, Late}	0.1
Distribution	{Normal, Dry-Spells, Two-Flushes}	0.1
Intensity	{Normal, Violent, Floods}	0.1
Others	{All Others}	0.05

The role of the Fuzzy Logic system here was that of linking the inputs with the outputs. For example, with an input of '*late rain onset' and 'rain direction being NOT(South-to-North)' accompanied by Scattered and from other directions lightening*. This gives a negative weight of 5 leading to the output '*Failed' rains*'. However, before sending this output to the users, all other indicators are also evaluated and output aggregated.

(b) **Implementation in MATLAB Fuzzy Logic Toolkit**

Input data for the 5 seasons and the output data for the 2 rain seasons was used to implement the fuzzy logic representation in MATLAB Fuzzy Toolkit. This was based on Mamdani's fuzzy inference method (Mamdani, S. 1975) and was achieved as follows.

All the Second Order Inputs were used to generate respective **Input Variables**. To fuzzify the inputs, **Fuzzy Member Function (FMF)** *smf* was used for increasing indicators (the larger the value, the better, for example, "*early onset of the MAM rains*"); FMF *zmf* for decreasing indicators (the larger the value, the worse the situation, for example, "*scattered lightening in all directions*"); and *imf* FMF for 'normal' (for example "*OND rains lasts until mid-December*").

Similarly, all the outputs were converted into **Output Variables** as defined in the Toolkit and later linked to the inputs using the weights in the two tables above and the Toolkit's pre-defined logic operations (AND, OR, NOT and so on).

Example:

If (Met Indicator On OND Rain Season Onset is Violent Non-Empty Thunder) and (Rain Direction is South To North) and (Frogs Croak In The Evening) then Rain Season Quality is (Favourable For Maize) Rain Season Onset is (Normal) and RainSeasonCession is (Normal)

Appropriate **Defuzzification Operations** (max, sum and probor) as supported in the Toolkit were used to revert to output formats that are comprehensible to the users. This output later guided the design of the database tables used to store the IK indicators and output.

(c) **Learning in Fuzzy Logic**

The main weakness of Fuzzy logic is the inability to learn or 'remember' (Chen, Anthony et al. 2008). This is addressed in MATLAB via the Adaptive Neuro-Fuzzy Inference System (ANFIS). ANFIS takes a fuzzy inference system (FIS) and tunes it with a back-propagation algorithm based on some collection of input-output data hence, allowing it to learn.

5.4 Data source 2: Structured Weather Data

5.4.1 Logic Design

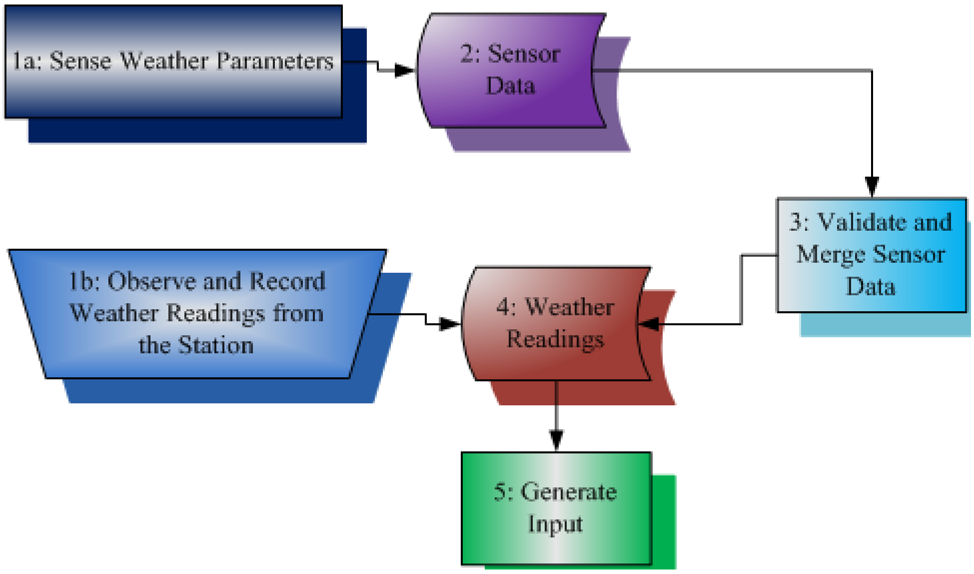


Figure 5-11: Structure Weather Data Logic Design

Step 1a: Data from the sensors is received by the SMS gateway which calls a PHP script that decodes the various parts of the messages and stores the sensor readings in a database the **Sensor Readings** store (Data Store 2).

Step 1b: After observing the hourly readings at the Weather Stations, the observer manually enters the readings to the system using a web interface. These readings are stored in a database the **Weather Readings** data store (Data Store 4).

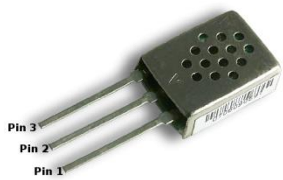
Step 3: Each entry in the Sensors Reading data store is extracted and examined for any discrepancies, for example, a reading from the temperature sensor which is much higher that the Board Temperature is usually flagged and therefore not exported to the Weather Readings data store. Further, similar (temperature for example) readings from sensors in the same location are aggregated to get the equivalent hourly readings; the aggregation is based on calibration decision made and discussed below. The validated sensor readings are then stored in the Weather Readings data store.

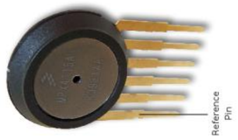
Step 4: With both the sensors and stations data in the same data store, various reports are generated to meet different user needs.

5.4.2 Calibrating Sensor Boards versus Weather Instruments

The acceptability of the data provided by the sensors by the meteorologists is only possible if the sensors are calibrated against conventional weather stations. In order to take care of this, calibration the sensors was carried out using conventional weather stations at KMD. The Chiromo Observatory (run by the Department of Meteorology, University of Nairobi) was used for the initial experiments. After the calibration exercise, the sensor boards were used to design a weather monitoring system described Implementation Chapter. The Observatory Unit of KMD is responsible for making weather observations of every kind. Among other duties this Unit runs a manual weather station that is operated 24 hours a day – 7 days week. Calibration experiments were conducted to evaluate the field readiness of the Libelium's ***Waspmote*** (Libelium, Comunicaciones, Distribuidas, S.,L. 2010) platform in terms of drought forecasting to support weather forecasting. The list of sensor used versus the weather instruments is shown in the table below.

Table 5-5 List of Sensor Boards versus Weather Instruments Calibrated

Weather Parameter	Sensor Board	Weather Instrument
Temperature	**Temperature sensor MCP9700A by Microchip**: is an analog sensor which converts a temperature value into a proportional analog voltage. 	**Mercury-in-glass thermometer**that has calibrated marks on the tube allowing temperature to be read by the length of the mercury within the tube. There is usually a bulb of mercury at the end ofthe thermometer which contains most of the mercury -this increases the sensitivity of the mercury to temperature changes.Expansion and contraction of this volume of mercury is amplified in the much narrower bore of the tube 
Relative Humidity	**Humidity sensor 808H5V5 by Sencera**: This is an analog sensor, which provides a voltage output proportional to the relative humidity in the atmosphere. 	At KMD, humidity is usually calculated by getting the difference between the dry-bulb temperature and the wet-bulb temperature. This difference is called the *wet-bulb depression* and is compared with *adjusted depression* which is tabulated. The ***humidity slide rule*** is then used to obtain Relative Humidity.

Atmospheric Pressure	**Atmospheric pressure sensor MPX4115A by Freescale**: It converts atmospheric pressure to an analog voltage 	**Kew-type station barometer**: acts directly on the surface of the mercury in the cistern, causing the mercury level in the column to rise or fall as the atmospheric pressure rises or falls. 

5.4.3 Calibration Model

In consistent with our overall methodology described in Chapter 3, the calibration followed a 3-steps experimental process with three types of experiments namely ***pilot experiments***, ***explanatory experiments*** and ***confirmatory experiments***. A systematic error analysis based on three error types: ***Mean Absolute percentage Error MAPE)***, ***Mean Error (ME)*** and ***Root Square Error (RSE)*** then followed. Inherent sensors errors that are inbuilt in the sensor boards were also checked. Finally, ***correlation coefficients*** and ***plots*** such as side-by-side boxplots were used for ***similarity tests***.

Pilot Experiments

The pilot experiments involved comparisons between the readings from the sensors with those from the manual weather station at the Chiromo Observatory. For each of sensor board, the readings of temperature, humidity and pressure were read every 30 minutes and stored in SD cards and a copy sent in form of text messages (SMS) to one of the author's phone number. The latter was used to monitor the sensors' activity. The sensors' readings were averaged after every hour and compared with those from the weather station. Below is a sample measure of similarities between the humidity.

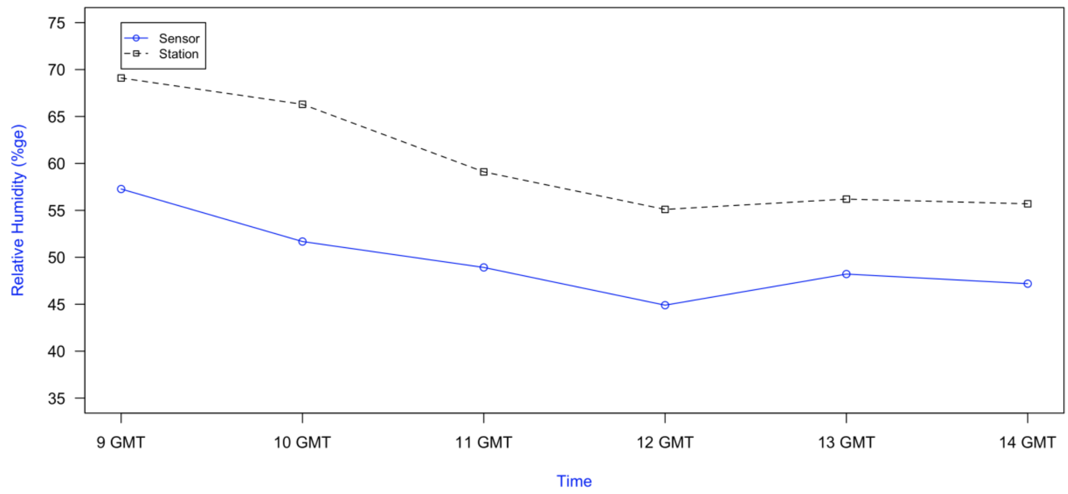


Figure 5-12: Pilot Phase: Humidity Readings Comparison

Exploratory Experiments

Having confirmed that sensors gave readings that correlated with those from the reference weather station, a series of four exploratory experiments were carried out to verify different aspects of the sensors' behaviour as described below.

Exploratory Phase I: These experiments were carried for a period of two weeks and the aim was to collect adequate dataset for computing MAPE and RMSE. This resulted in MAPE values of below 5% and RMSE values less than 1.2 for all the sensors.

Exploratory Phase II: To further increase data sample size, a second set of exploratory experiments were run at the KMD Headquarters in Nairobi where unlike the Chiromo station, readings are taken twenty four hours a day, seven days a week. The MAPE and RMSE values attained matched those in Exploratory Phase I. The sensor readings were also found to be consistent (correlation coefficient of over 0.9) with those from the weather station.

Exploratory Phase III: In preparing the sensors for the real world, sensor enclosures were designed and built at the University of Nairobi's Science Workshop located within Chiromo Campus. After consultations with the experts at the University of Nairobi's Science Workshop, Perspex material was recommended. Further, this experiment set out to find out the relationship between the Board Temperature (taken using the function ***RTC.getTemperature***) and the value from the temperature sensor. The outcome here was that enclosures made from Perspex material affected the operation of the sensors; the idea of using a mini-*Stephenson Screen* is being pursued in the future improvements of this research. On the issue of Board Temperature, a correlation between this reading and the one from the temperature sensor was noticed; the latter tends to be less than the earlier by 1.5 to 1.7^{o}C. This knowledge was incorporated in the program code running in the sensors to detect when the temperature sensors gave erroneous readings (way above or below the board temperature reading)

Exploratory Phase IV: After two months of experiments, basic procedures of using the sensors had been finalised. These included; how often to charge/change batteries, where/how to place the sensors, how often the readings were observed and sent to the SMS gateway, system prototype to receive the readings and so on. With all these in place, sensors were left in field for a period of four weeks. This dataset was used to make various calibration decisions and adjustments explained below.

5.4.4 Calibration Experiment Setup

Reading Formats: Each sensor board was fitted with temperature, relative humidity and pressure sensors. Apart from taking readings from these three sensors, the board temperature, battery level and current date/time were read using; RTC.getTemperature(), PWR.getBatterLeve() and RTC.getTime() commands respectively. Each sensor was programmed to take readings at an interval of 30 minutes after which it would go to sleep. This took format:

Date-Time; Temperature; Board Temperature; Humidity; Pressure; Battery Level

Example:

Thursday, 11/09/21 - 09:30.07;20.32;24;50.34;843.58;98

Representing readings of 20.32 for temperature sensor, 24 for Board Temperature, 50.34 for humidity, 843.58 for pressure and 98% of battery power.

Further, each set of readings (excluding the date/time) were also stored in the SD Card. After every one hour (2 readings), sensor boards sent the two previously stored reading sets as an SMS via GPRS. The current date/time would then be included in this SMS yielding the format:

Date-Time; Temperature; Board Temperature; Humidity; Pressure; Battery Level

Temperature; Board Temperature; Humidity; Pressure; Battery Level

Example

Wednesday, 11/09/21 - 10:30.45;20.96;26;50.97;849.13;91

23.87;25;46.56;841.36;88

This resulted in a text message of about (depending on the day of the week, for example Monday is shorter than Saturday) 80 characters. These hourly readings were sent to a GSM modem that was linked to an SMS Gateway through which the readings were sent to a database running on Ms. SQL Server.

Recording GPRS Delays: In order to compute the amount of time spent on sending an SMS, timestamps at the beginning and at the end of the sending process were recorded and stored in a file. These took the format:

TimeStamp Before Sending; TimeStamp After Sending

Example:

Thursday, 11/09/27 - 01:14.24; Thursday, 11/09/27 - 01:14.46

Weather Station Data Collection At the Observatory Unit of KMD, weather readings are taken and recorded in a book on hourly (at 15 minutes to the hour, for example, 12:45) basis. At the end of the experiment, a copy of these entries was obtained and the readings manually entered on excel sheet. The readings extracted were: Temperature, Dewpoint and Pressure. Applying equations[13], 5-1, 5-2 and 5-3 Relative Humidity values were computed using the Temperature and Dewpoint values. The equations involve the calculation of saturation vapour pressure (Es) and actual vapour pressure (E) in millibars.

Equation 5-1: Computing E_s

$$E_s = 6.11 * 10.0^{\left(\frac{7.5 * T_c}{237.7 + T_c}\right)}$$

Equation 5-2: Computing E

$$E = 6.11 * 10.0^{\left(\frac{7.5 * T_{dc}}{237.7 + T_{dc}}\right)}$$

Equation 5-3: Computing RH

$$RH = \frac{E}{E_s} * 100$$

Where * is multiplication sign, RH is Relative Humidity, T_c=air temperature in degrees Celsius and T_{dc}=dewpoint temperature in degrees Celsius.

[13] http://www.gorhamschaffler.com/humidity_formulas.htm

5.4.5 Calibration Experiment - Data Analysis

(a) Reading Time Lags

Though programmed to sleep for 30 minutes, the sensors had time lags due to various computation tasks such as:

- Delay statements used for stabilising power supply after waking up
- Writing to SD card
- ***print*** and ***println*** statements.
- GPRS commands

The time lags ranged between 8 and 47 second and this kept on increasing as the size and number of output files increased. Since this would render the readings unacceptable by the by the World Meteorological Organisation which allows a maximum of 15 minutes delay, the lags were resolved through re-programming the sensor boards. For example, given that on average the sensor had time lag of ***8.645 seconds***, an adjustment of 7 seconds was factored into its sleeping time; altering

const * sleep_duration = “00:00:30:00”; to: const * sleep_duration = “00:00:29:53”;

(b) Sensor Versus Weather Station Data Analysis

Sensor versus Weather Station Data: given that sensor boards were fitted with 3 sensors each; Temperature, Humidity and Pressure and that each sensor took readings every 30 minutes; each sensor had 2 reading for each parameter per hour.

For example, assuming three Sensor Boards at were installed at KMD Headquarters, on a given date and time (say October 10, 2011 at 15:00), the sensors would output six Temperature readings; two from each temperature sensor mounted on each of the three sensor boards. In order to compare these with the equivalent hourly readings from the weather station, aggregate values for each parameter were computed using Option1 and Option 2 described in Chapter 3.

Below is an illustration of error analysis for using Option 1.

i. Error Analysis

Table 5-6 Comparison Option 1 Error Analysis

Error Type	Temperature Sensor	Humidity Sensor	Pressure Sensor
Mean Error (ME)	1.54	6.52	-12.80
Mean Absolute Percentage Error (MAPE)	8.21%	9.58%	1.35%
Root Mean Square Error (RMSE)	1.63	8.31	12.83

ii. Sensor Readings Adjustments

Three options of adjusting the errors in the table above were attempted: using ME, MAPE and RMSE; the adjustments using MAPE had the greatest gradient and therefore adopted for the final adjustment as shown in the expression below:

$$AdjustedTemp_t = OriginalTemp_t + (OriginalTemp_t * MAPE/100);$$

The adjusted temperature reading for each sensor taken at time *t* is computed by adding a weight factor equivalent to the respective Mean Absolute Percentage error. That is, 8.21%, 9.58% and 1.35% for temperature, humidity and pressure respectively. These changes were effected on the entire dataset after which the process of computing the errors was then repeated resulting in the following values:

Table 5-7 Option 1 Error Analysis after MAPE Factor Adjustment

Error Type	Temperature Sensor	Humidity Sensor	Pressure Sensor
ME	0.08	1.04	0.17
MAPE	3.35%	6.14%	0.08%
RMSE	0.74	4.30	0.87

iii. Similarity Tests

In order to graphically view the similarities between sensor and station readings, graphs similar to the ones below were plotted for both before and after MAPE adjustments described above.

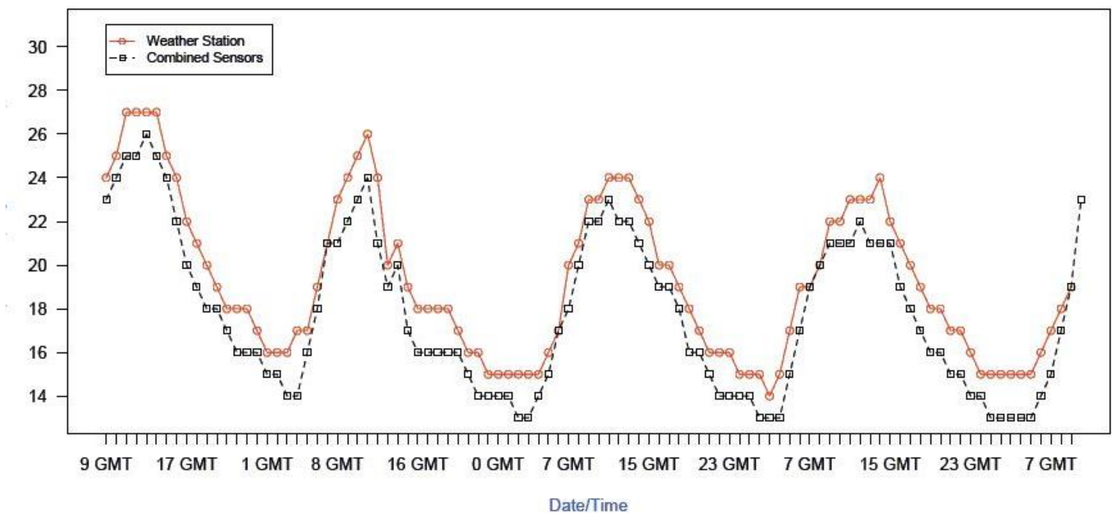


Figure 5-13: Option 2: Temperature Sensor Comparison with Station

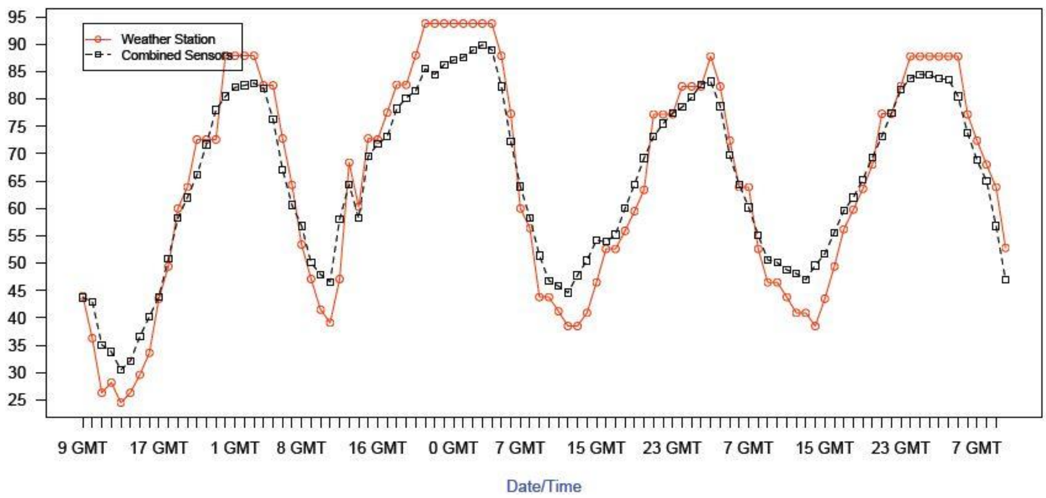


Figure 5-14: Option 1: Humidity Sensor Comparison with Station

5.4.6 Confirmatory Experiments

(a) Experiment Set up

After all the necessary adjustments performed during the exploratory experiments, a confirmatory experiment was run with the sensor boards installed within the KMD Observatory Unit. Experiment setup similar to one used during the Exploratory Experiment IV was used; readings from the weather station for the same period were keyed in manually. The objectives here were to first 'confirm' that the adjustments proposed were the best and two, to choose between the two options of aggregating sensor readings. In this phase, the adjustments were factored into the program code and loaded onto the sensors.

Example, Temperature Sensor: the individual errors for each Board were used:

```
//Factor in MAPE of 8.21% =0.0821
value_temp=value_temp+ (value_temp*0.0821);
```

(b) Selecting the Better Option

Before reaching the final decision as to which of the two options (of combining sensor data), further analysis were carried out as explained below.

i. **Error Analysis Summary**

Table 5-8 Confirmatory Experiment - Error Analysis Summaries

Error Type	Option	Temperature	Humidity	Pressure
MAPE	Option 1	8.55	12.54	1.47
	Option 2	8.53	11.90	1.47
RMSE	Option 1	1.96	10.94	12.06
	Option 2	1.89	10.56	12.10

For temperature and humidity sensors, Option 2 performed better for both MAPE and RMSE. However, though Options 1 and 2 had equal performance (1.47) for pressure sensor using MAPE, Option 1 outperformed Option 2 under RMSE (12.06 versus 12.10). Based on some discrepancies noted for the pressure readings during the experiments (the details are discussed in the Further Work Section), the discrepancy above was ignored and a decision to pick Option 2 as the best way of combining the sensor readings reached.

ii. **Correlation Coefficients**

To further validate the choice of Option 2, the correlation coefficients of the sensor readings with the weather station were computed.

Table 5-9 Confirmatory Experiment - Correlation Coefficients

Options	Temperature	Humidity	Pressure
Option 1	0.924	0.920	0.723
Option 2	0.940	0.936	0.657

Again, except for the pressure sensor, Option 2 had the highest correlation coefficients.

5.4.7 Calibrating the Sensors

Using Option 2, the MAPE error factors of 8.53% and 11.90% for temperature and humidity respectively were used to calibrate the sensors. These values were used to update the program code as follows:

```
value_temp=value_temp+ (value_temp*0.0853);
value_humid=value_humid+ (value_humid*0.119);
```

Similarly, though not the lowest, the Pressure MAPE value (1.47) for Option 2 was used. The decision was reached for uniformity purposes and also the fact that the Option 1 value (1.46) was close to this one. The code therefore looked like this:

```
value_pressure=value_pressure- (value_pressure*0.0147);
```

5.4.8 Battery Management Tests

The sensor boards employed in this research make use of chargeable lithium batteries for power. In order to determine how often to charge/replace the batteries, a series of experiments were performed to answer the following questions:

i. How long does it take to charge a battery that is almost depleted?
ii. How long does a fully charged battery run when used on a sensor board with various sensors installed and under different operation modes(for example, SLEEP_MODE Nr OFF)?
iii. How do various environmental conditions (cold, rainy, hot and so on) under which the sensor boards are operating affect the batter power?

Some of the results attained included:

i. It took an average of twenty hours to fully charge a battery that is almost completely depleted;
ii. A battery powering a sensor board that has four sensors: temperature, humidity, pressure and GPRS and set to operate with SLEEP_MODE (wakes up every 30 minutes to take readings) set to ON, would use up to 60% of the battery power within one week. It would take about 24 hours to reach the same battery level with SLEEP_MODE set to OFF; and
iii. At about 38% power level, a battery would experience problems powering the GPRS.

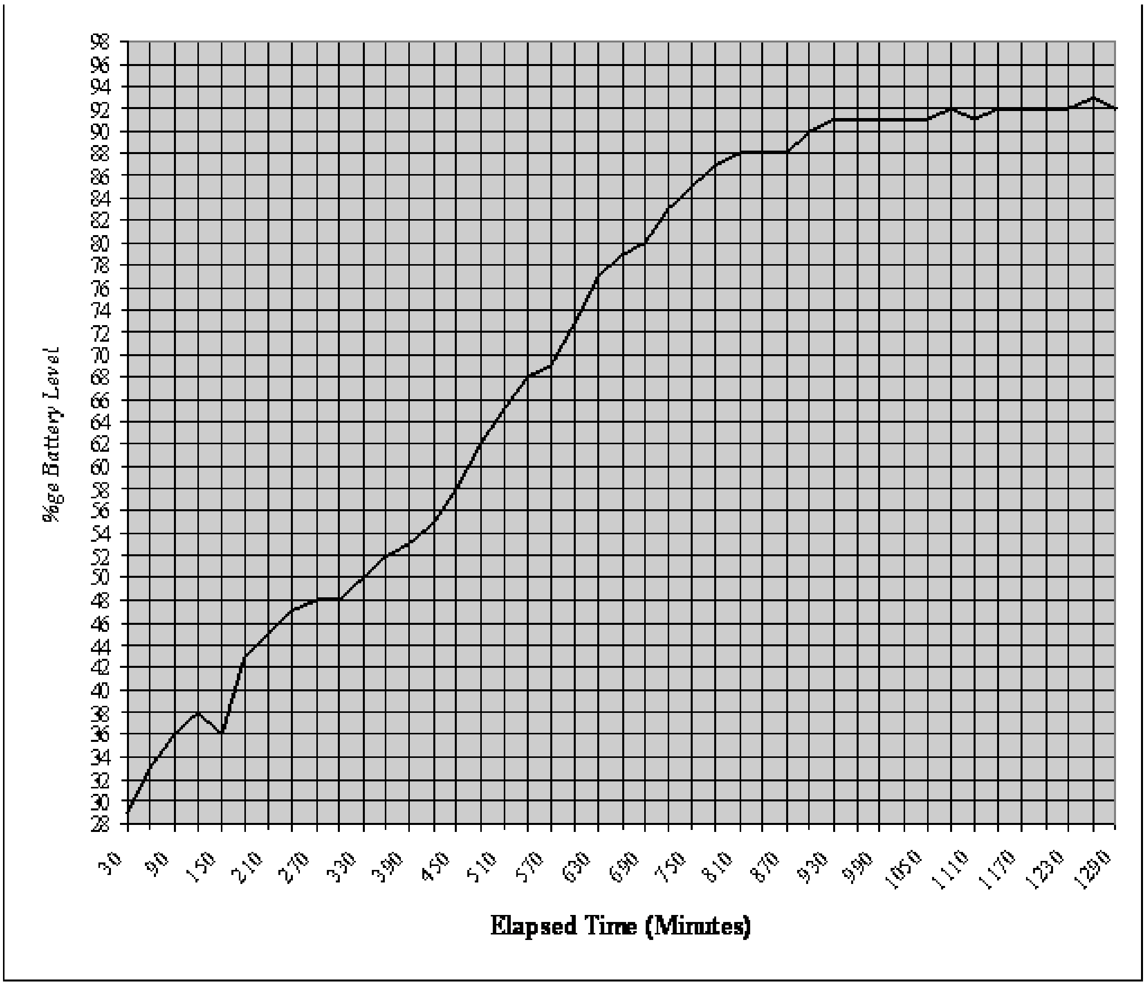


Figure 5-15: Battery Power Management – Charging Curve

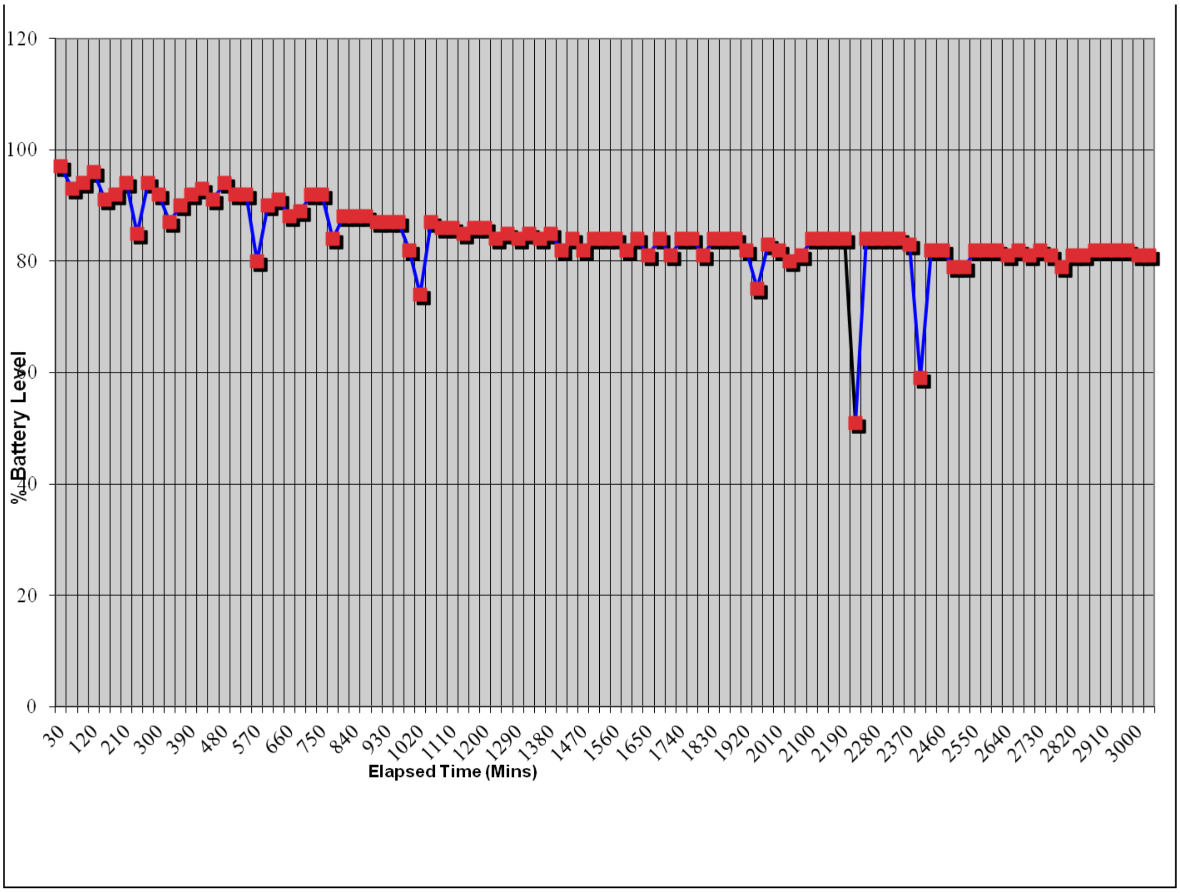


Figure 5-16: Battery Power Management – Depletion Curve

5.4.9 Post Deployment Errors

After the calibration exercise, the sensors were deployed at 4 locations in Kenya. The aim was to further observe the adherence to the adjustments reached during the calibration as well as find out any other operational issues the sensors may have had. Each of these locations has a conventional weather station with which to compare the sensors readings. The analysis of post-calibration phase is shown below.

Table 5-10: Post-Calibration Error Analysis

Sensor/ Error Type	**Temperature**	**Humidity**	**Pressure**
MAPE	4.45	8.89	0.10
RMSE	1.21	6.57	1.09
ME	0.03	0.40	0.19

This implies that when the sensor gives a reading of say 25^{0}C, the value carries with it an error of 4.45% (±1.1^{0}C).

6. Drought Monitoring using Effective Drought Index

Assessment of droughts is of primary importance for freshwater planning and management. This requires understanding historical droughts in the region as well as impacts of droughts during their occurrences… the onset and the end of a drought are difficult to determine, the impacts of a drought increase slowly, often accumulate over a considerable period and may linger for years after termination. Therefore, a drought is often referred to as a creeping phenomenon (Mishra, Singh (2010) *page 2)*

6.0 Introduction

The second component of the Integrated DEWS Framework presented in Chapter 4 is '***Drought Monitoring and Prediction'***. ***Drought Monitoring*** is described in this chapter while ***Drought Prediction*** is handled in Chapter 7. In particular, this chapter goes into great length to qualitatively and quantitatively analyse the past droughts that occurred in Kenya for the last 40 years using Effective Drought Index (EDI). In doing so, we proof that EDI is an effective tool for not only qualifying/quantify droughts but, when used together with various weather forecasting products in use today, it is a valuable complementary tool in weather-related decision making processes. This chapter also lays the ground work for the use of EDI as the main input and output to the ANNs-based drought prediction presented in the next chapter.

In line with the methodology described in Chapter 3, the analysis of the weather data using EDI was carried out in three phases: Phase 1, data for Embu Station was used to ***pilot*** the approach, while in Phase 2, data for Dagoretti, Embu and Makindu Stations was used to run ***exploratory studies*** and finally, data for Kakamega was used to confirm (***confirmatory***) the findings. To start off, past droughts (and some floods) that affected Kenya between 1981 and 2009 were analysed in this chapter. Kenya was selected because for the last two decades, the Country has consistently contributed the highest number of people affected by natural disasters in Africa (Deely, David et al. 2010; Masinde, Bagula 2011)

Among other facilities, KMD runs 27 synoptic stations from which an array of weather parameters is recorded on hourly and daily basis. Data from some of these stations was used to demonstrate the power of EDI in profiling droughts. Later in the implementation chapter, a user-friendly website that was created to show how presenting daily precipitation values side by side with drought classes and AWRI values can aid in decision making process is presented. By comparing the attributes of EDI with both the Seasonal Climate Forecasts (SFCs) and the ***Dekad Rainfall Summaries*** regularly issued by KMD, it emerges that EDI can play a critical role in complementing weather-related decision-making.

6.1 Computing Effective Drought Index

In EDI, daily precipitation height values and Effective Precipitation (EP[14]) are used to compute **deficiency** or **surplus** of water resources for a particular date and place. The latter implies that EDI does not only detect droughts, but floods too. EP makes use ***Equation 2-1*** in Chapter 2. To be able to relate the EPs of a given weather station with climatological data, they are averaged along the day number (i.e. by calendar day). For instance, when using data for 1979 to 2009, the climatological mean for 28 March is the average for the 28 March 1979, 28(March 1980, …, 28th March 2009.

EDI quantifies droughts in terms of **droughts classes** composed of positive and negative real values; for example, **-2.50** indicates **extreme drought**, **+3.28** indicates **extreme floods** and **0.98** indicates **close to normal wetness**. EDI further qualifies climatic/weather variations by providing **Available Water Resource Index (AWRI)** that can for example reliably inform a farmer of the amount of water in the soil at any given day. Computation of EDI is made with consideration of the fact that the quantity of rainfall that can be used as a water resource drops gradually over time after the rain has fallen.

EDI Computation Steps

Starting with daily precipitation data for 31 years, EDI computational Steps are as follows:

i. Calculate EP_i
ii. Calculate 30 year Mean EP (MEP) for each calendar year
iii. Calculate the deviation of EP (DEP) from MEP; DEP=EP-MEP
iv. Negative DEP means dry; add the days of prolonged dryness to existing period
v. Calculate the standard value of DEP that is SEP) as SEP=DEP/ST (EP); this is the standard deviation of each day's EP. This standardisation enables comparisons of

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14 The EP is the summed value of daily precipitation with a time-dependent reduction function

drought severity in diverse climatic zones. That is, the values have universal meaning irrespective of climatic differences.

vi. To get EDI, divide DEP for each calendar day by standard deviation over the past 30 years.

Table 6-1: Characteristics of indices associated with EDI

Name	Calculation	Meaning
Mean of EP (MEP)	30-yr mean of EP for each calendar day	Climatological mean of water quantity
Deviation of EP (DEP)	DEP = EP - MEP	From climatological mean, the deficit of water quantity
Standardised value of DEP SEP)	SEP = DEP/ST (EP)	From climatological mean, standardised deficit of water quantity
Consecutive days of negative SEP (CNS)	Consecutive days of negative SEP	Shows how long precipitation has been in deficit
Precipitation needed for a return to normal (PRN)	Calculated using Equation (2)	Precipitation needed for a return to normal conditions.
Effective Drought Index	Calculated using Equation (3)	The standardised deficit or surplus of stored water quantity.

Equation 6-1: Precipitation to Return to Normal (PRN) Equation as used in EDI

$$PRN_j = \frac{DEP_j}{\sum_{N=1}^{j}\left(\frac{1}{N}\right)}$$

Equation 6-2: Effective Drought Index Equation

$$EDI_j = \frac{PRN_j}{ST(DEP_j)}$$

The EDI expresses the standardised deficit or surplus of stored water quantity and therefore enables one location's drought severity to be compared to another location's, regardless of climatic differences. Once the EDI_i are computed, their respective drought classes are computed using the following steps:

EDI Drought classes Criterion

Extreme drought - EDI <-2.0

Severe drought - -2.0 ≤ EDI <-1.5

Moderate drought - 1.5≤ EDI <-1.0

Near normal - 1.0≤ EDI <-1.0

As shown below, the interpretation of EDI values should put into consideration season under consideration

Table 6-2: Season Sensitive EDI Classification

In spring	-0.5 > EDI : Moderate Drought -1.0 > EDI : Severe Drought -2.0 > EDI : Extreme Drought
In rainy season	-1.0 > EDI : Moderate Drought -2.0 > EDI : Severe Drought -3.0 > EDI : Extreme Drought
Other season	-0.7 > EDI : Moderate Drought -1.5 > EDI : Severe Drought -2.5 > EDI : Extreme Drought

Monthly EDI

Though designed to calculate drought indices on daily basis, the principles can be used similarly with monthly time step data as has been described in Smakhtin, Hughes (2007). In this case monthly (not daily) EDI is a function of precipitation needed for a return to normal conditions (PRN), i.e. for the recovery from the accumulated deficit since the beginning of a drought. PRN, in turn, is related to monthly effective precipitation (EP). The EP equation (Equation 4-1) above is applied in a similarly way as in the daily EDI but now the $\boldsymbol{i_s}$ represent months and not days.

6.2 Application of EDI - Kenya's Case Study

6.2.1 Weather and Droughts Forecasting in Kenya

As Abdishakur Othowai put it (Collins, Nick et al. 2009), "*Weather is upside down in Kenya*". He was referring to the noticeable climatic variability that has greatly undermined the traditional seasons that Kenyans have always relied on. Analysis of precipitation data for years 1979 to 2009 from three weather stations in Kenya attests to this fact. Rains no longer fall when they are expected; for instance, the March-April-May rains generally begin by mid-March but in 2011, this did not happen until early May for most areas in Kenya. Droughts are the most common disasters in Kenya; they result from variations in weather/ climate, but there are occasional floods too. In the period 1999 to 2008, Kenya contributed a whopping **32.85%** of people affected by natural disasters in the Africa (Collins, Nick et al. 2009). In August 2011, Kenya was among the countries at the Horn of Africa that experienced a devastating drought that was described as "*the worst drought in 60 years*[15]". Such disasters cannot be avoided but can be managed through effective early warning systems. When they occur, droughts affect more that 25% of Kenya's population not mentioning the ripple effects such as inadequate hydro-electric power supply, increased commodity prices and loss of jobs just to mention a few. The level of preparedness is determined by how well the disasters are defined and their characteristics quantified. The latter is currently lacking and this is the lacuna this chapter fills.

Kenya has two main rainy seasons: (1) October-November-December (OND); (2) March-April-May (MAM); MAM is the main season. Sometimes the rainfall may occur in the period June-July-August (JJA). Among other factors (not part of this research work), the amount of rain in each of the above season is used to classify Kenya into 14 Climatic Zones (http://www.meteo.go.ke). Currently, monitoring of climatic/weather variations in Kenya is the mandate of the Kenya Meteorological Department. The Department runs three main types of stations that are currently managed by the Climatological Section of the Department (http://www.meteo.go.ke/):

- 700[16] rainfall stations,

15 http://www.bbc.co.uk/news/world-africa-13944550

16 There were 2,000 rainfall stations in Kenya in the year 1977; the drastically dropped to 1653 by the year 1988 and to 1497 by 1990; now there only 700.

- 62 temperature stations and
- 27 synoptic[17] stations.

The Agrometeorological Section on the other hand manages 13 stations related to agriculture; data is remitted from these stations every 10 days. Apart from the normal meteorological observations, other observations by the Agrometeorological Section include: soil temperature, sunshine duration, radiation, pan evaporation and Potential Evapotranspiration. All this data is stored in semi-automated formats at the Department's Headquarters in Nairobi. The data is available to interested stakeholders on request. The data used in this research was obtained from this Department.

The Meteorological Department uses the data collected to provide five main types of forecasts such as daily for main cities/towns in Kenya, 4 and 7-day as well as monthly and seasonal. The 4-day, 7-day and monthly forecasts are in form of downloadable pdf reports summarising the recent past, current and near-future weather patterns in conceptual terms. The season forecasts are more detailed and they are also provided in the Swahili language; sample detailed seasonal forecast is in ***Appendix 11-1***. The Department also works hand in hand with both the print and electronic media to disseminate the forecasts.

6.2.2 Existing Gaps

Non-User Centred Weather Forecast Information: The forecast information is supply-driven and its usefulness to key stakeholders especially the farmers and policy formulators is rather wanting. It would for example be desirable if the Department could inform the relevant government ministries the actual implications (in operational quantifiable terms) of weather observations. It is not enough to report that; "*60.4mm of rainfall was recorded in Kakamega"*; instead, a report saying, "*60.4mm of rainfall that was recorded in Kakamega raised the available water resource to above the normal for this area. It is predicted that the rains will continue for a week and this will lead to severe floods in the low-lying areas of the Kakamega*". The latter is more useful and can be used by policy formulators to mount rescue operations. As

[17] Synoptic stations are those which observe and record all the surface meteorological data; rainfall, temperature, wind speed and direction, relative humidity, solar radiation, clouds, atmospheric pressure, sun shine hours, evaporation and visibility

demonstrated later in this chapter, proper use of EDI can fix this gap by complementing both the seasonal forecasts and Dekad reports.

Ineffective Information Dissemination: The channels that are used to disseminate the forecast information are ineffective; the farmers that need it most do not get it and those that do, cannot comprehend the information. The current research attempts to fix this problem by use of user-centred tools to provide custom forecast information to farmers via mobile phones. Details of this appear in the Implementation Chapter in this dissertation.

Poor Coverage by Weather Stations: The third gap is as a result of the small number of weather stations installed. The 27 synoptic stations are far too few for the vast 582,650km^2 that is Kenya's geographical area. This makes it difficult to get the micro-level weather indicators that are necessary for effective forecasts. The current research fills this gap by introducing more cost effective and more automated wireless sensors networks as a complement to the weather stations' sparse network. The realisation of this was explained in Chapter 5.

6.2.3 Data and Methodology Used

Using data completeness as the main criteria, 4 stations were selected for the current research: two in Zone 11 (Dagoretti and Embu), one in Zone 14 (Kakamega) and one in Zone 10 (Makindu). Daily precipitation data for years 1979 to 2009 (and from 1968 for some stations) from these stations was used. From the analysis discussed in the subsequent sections, it emerged that apart from the **1984-1985 drought** and the **1997-1998 floods** that are focus of this chapter, more droughts occurred in some periods in 1980, 1982, 1999, 2000, 2001, 2003 and whole of 2008 to 2009. The 2008-2009 drought had in particular very catastrophic effects on the livestock-keeping communities.

Table 6-3: Geo-Data of the Weather Stations Studied

Name	Dagoretti	Embu	Kakamega	Makindu
WMO Number	63741	63720	63687	63766
ICAO	HKNC	HKEM	HKKG	HKMU
Year Opened	1954	1975	1957	1904
Latitude	01 18S	00 30S	00 17N	2 17S
Longitude	36 45E	37 27E	34 47E	37 50E
Elevation	1798 m	1493m	2133m	1000m

Two Phases: (1) Data cleaning; (2) Data analysis; were carried out as per the flow chart shown in **Figure 6-1**. A Java program was written to covert the original format to more friendly formats acceptable by the EDI Fortran program: (http://atmos.pknu.ac.kr/~intra2/down_src.php (lastly accessed on 10 October 2012). This FORTRAN program uses equations 2.1, 6.1 and 6.2 to compute daily/monthly EDIs and outputs them into text files.

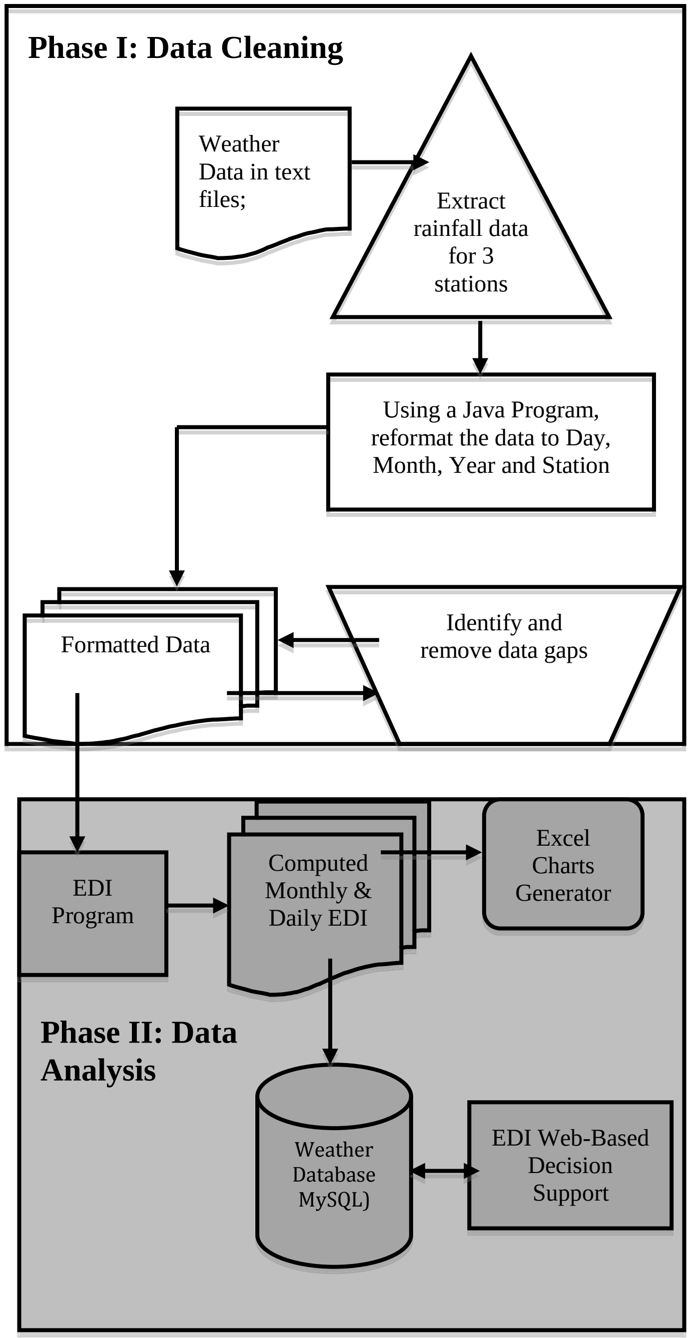


Figure 6-1: Data Cleaning and Analysis Flow Chart

Two versions of the EDI program were used:

Monthly EDI: This was used to calculate monthly EDI using monthly precipitation totals for 31 years (1979 to 2009). For each of the 3 weather stations, an Input File with the following format was processed using the EDI program.

Table 6-4: Monthly EDI Input File Format

Year	Month	Total Precipitation
1979	1	70.80
…	…	…
1979	12	68.80
1980	1	39.30
…	…	…
2009	12	121.10

Using modified (to replace days with months) equation 2-1, EDI computes the '*normal'* monthly precipitation for each calendar month of the year based on the mean of precipitation of this calendar month for all the 31 (of historical data) years. For example,

Normal precipitation for November is the mean of the precipitations for November 1979, November 1980, November 28 1980, …, November 2009.

Obviously, a '*normal'* precipitation for *November* in Embu may not be compared with the '*normal'* precipitation for *November* for Makindu; the two are in different climatic zones. The EDI values solve this by use of standard deviation to compute universal real values that have similar meaning in all climatic zones. Therefore, an EDI value of -2.59 will represent 'Extreme *Drought'* irrespective of climatic zones. For each of the stations, an Output File was generated, each showing the Effective Drought Index (EDI) and Available Water Resource Index (AWRI) calculations for 30 years 1980 to 2009).

Table 6-5: Monthly EDI Output File Format

Date	Total Precipitation	AWRI	EDI
1980-01-15	70.80	230.0	-0.51
1980-02-15	13.0	179.7	-0.65
1980-03-15	37.9	170.1	-0.86
1980-04-15	105.9	229.8	-1.35
…	…	…	…
1980-12-15	33.5	460.8	1.05
1981-01-15	14.6	364.9	0.37
…	…	…	…
2009-12-15	121.10	297.5	-0.27

i. **EDI-Interpretations**

EDI applies a time-dependent reduction function in computing the monthly/daily water deficiency. This is to cater for runoff and evapotranspiration that progressively reduces soil moisture over time. In Table 6-5, for example,

Available Water Resource Index for December 1980 was 460.8.

A total of 14.9mm of precipitation was received in January 1981

Simple Summation of monthly precipitation would have yielded 475.7

But factoring in runoff and evapotranspiration EDI yielded 364.2

ii. **Climatic Zone Interpretations**

The value of EDI is determined by the climatic conditions of a given zone and period/season. For example:

In March 1980, the AWRI for Dagoretti was 170.1. This translated to a Drought-Near Normal of -0.86

In April 1980, the AWRI for same station was 229.8. This was equal to a moderate tending to severe drought (worst) of -1.35.

The reason for this is that April is generally a wet month; in a normal March-April-May rain season, rains will have been falling for a whole month and therefore April is normally a wet month.

Daily EDI: This was used to calculate EDI for each calendar day of all the 31 years. Daily precipitation totals for each of the 3 weather stations were used; the Input File had the following format:

Table 6-6: Daily EDI Input File Format

Year	Month	Day	Total Precipitation
1979	1	1	0
1979	1	2	0
…	…	…	…
1979	1	29	35.2
	…	…	…
1979	12	31	0
…		…	…
2009	12	31	0

Using equation 2-1, EDI computes the normal daily precipitation for each calendar day of the year based on the mean of precipitation of this calendar day for all the 31 (of historical data) years. Like in the case of monthly EDI, the ‘*normal’* precipitation for *March 28* (picked because it is the birthday of the author) is the mean of the precipitations for *March 28 1979*, *March 28 1980*, *March 28 1980*, …, *March 28 2009*. Similarly, an Output File for each of the stations with the following format was generated.

Table 6-7: Daily EDI Output File Format

Date	Total Precipitation	AWRI	EDI
1980-01-01	0.0	117.0	-0.66
1980-01-02	0.0	115.4	-0.65
…	…	…	…
1981-01-31	0.0	208.1	0.96
1981-01-01	0.0	206.0	0.89
1981-01-02	0.0	204.0	0.81
…	…	…	…
2009-12-31	26.6	146.7	-0.20

In order to visualise drought in terms of classes described by Byun and Wilhite (1999) the following adapted classification was used:

- Extremely Flood EDI >2
- Severe Flood 1.5 < EDI < 1.99
- Moderate Flood 1 < EDI < 1.49
- Wet-Near Normal 0.01 < EDI < 0.99
- Drought-Near Normal -0.99 < EDI < 0.00
- Moderate Drought -1 < EDI < -1.49
- Severe Drought -1.5 < EDI < -1.99
- Extreme Drought EDI<-2

In the web-based system described later in this chapter, colour-coding (ranging from dark-red representing ‘Extreme Drought’ and dark-blue representing ‘Extreme-Floods’) was used to represent drought classes.

6.3 General Findings

6.3.1 **Annual Precipitation, EDI and AWRI Variations**

With a value of 1,923, Kakamega has the highest mean followed by Embu, Dagoretti while

Makindu receives the least amount rainfall. The following three charts show the annual distribution of the rainfall.

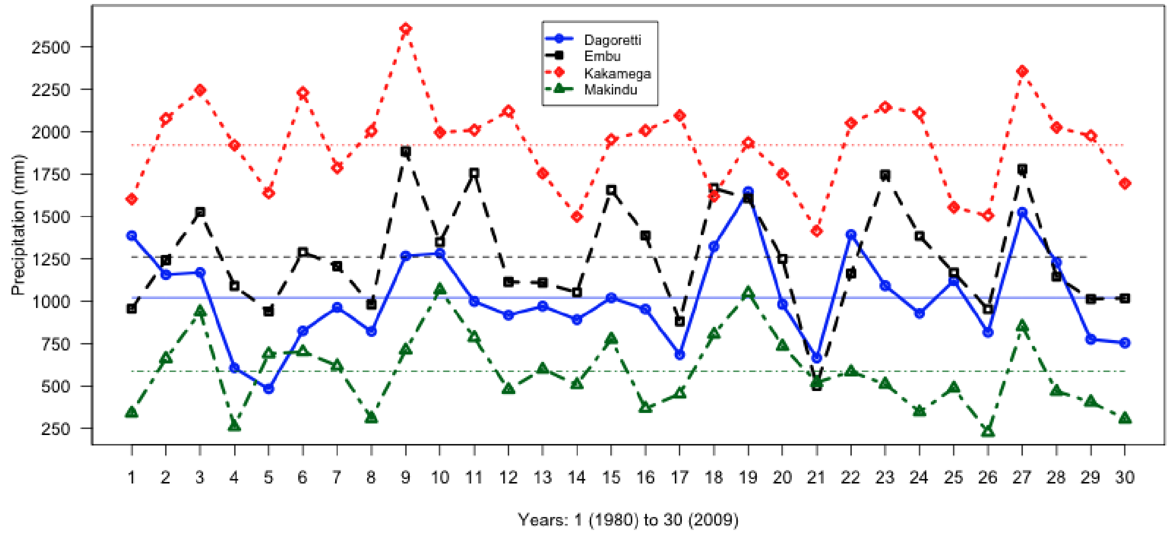


Figure 6-2: Annual Precipitation Variation for 1980 to 2009

Though the figure above shows that Kakamega, this is purely based on the climatic zone (14) where it is located. By extension, 100mm of rainfall received in Kakamega does not have the same effect as 100mm received in Makindu. Using EDI values, it is possible to know the actual effects of this precipitation as shown below. The annual average EDI values used to plot the graph below were derived from all the daily EDI values for each year.

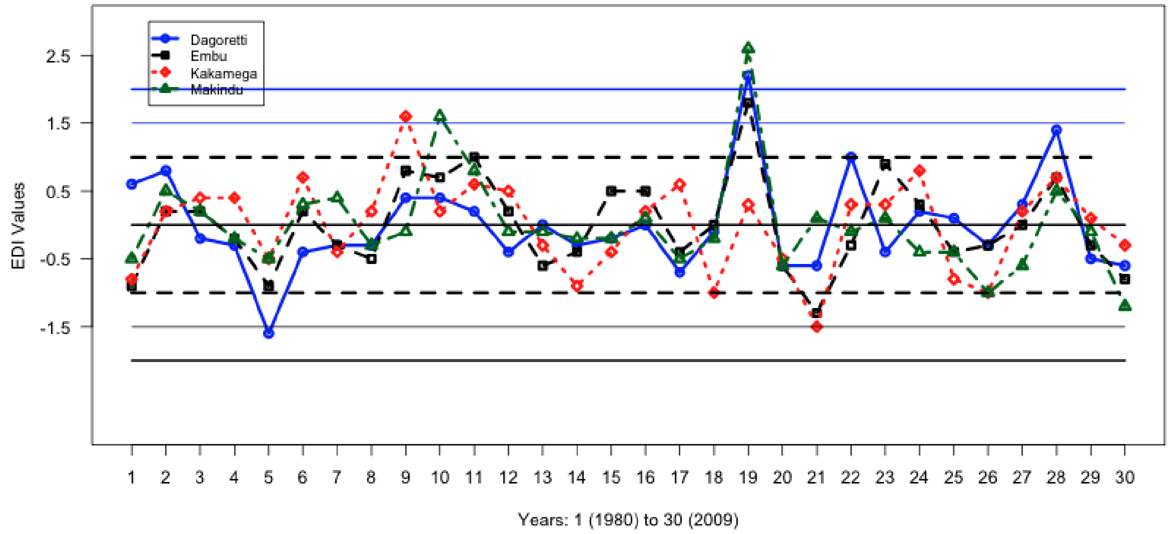


Figure 6-3: Annual EDI Variation for 1980 to 2009

Similar to the EDI graph above, AWRI values were used to further map the differences between the precipitation patterns in the four weather stations as shown below:

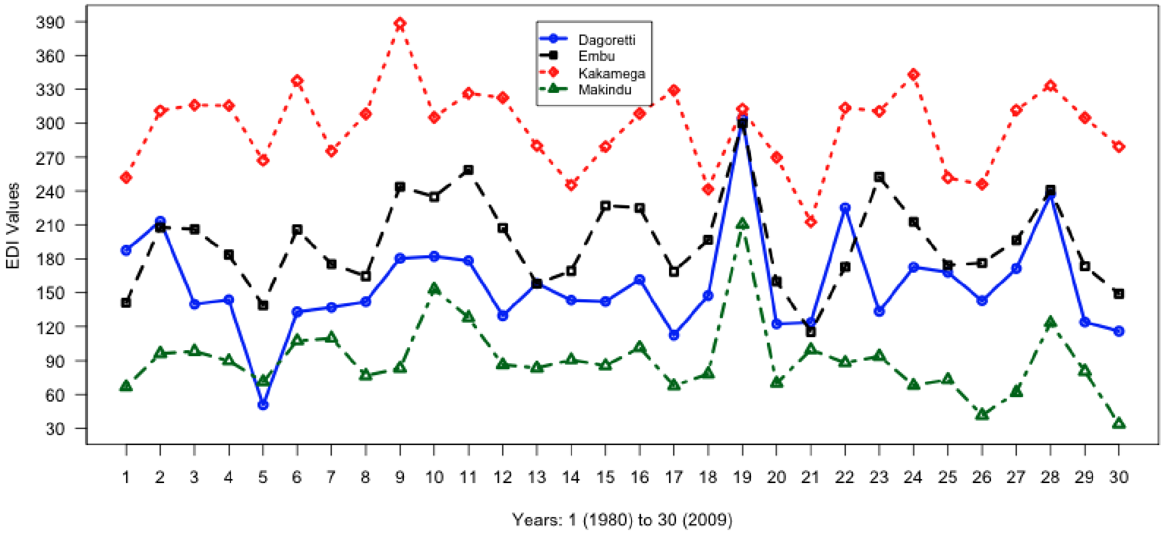


Figure 6-4: Annua1 Precipitation Variation for Embu

To further demonstrate the ability of EDI to map climatic variations, box plots for the four stations for Precipitation, EDI and AWRI were also used.

6.3.2 Identifying Extreme Events

EDI values equal or greater than 2 represent **extreme floods** while values less or equal -2 is an indication of **extreme droughts**. From the graph below, there are many extreme weather events that occurred between 1980 and 2009. Only extreme events that occurred in at least two of the stations and lasted for at least six months that were considered for further analysis. These are:

i. 1983 – 1985 drought

ii. 1998 – 1999 floods

iii. 2008 – 2009 drought

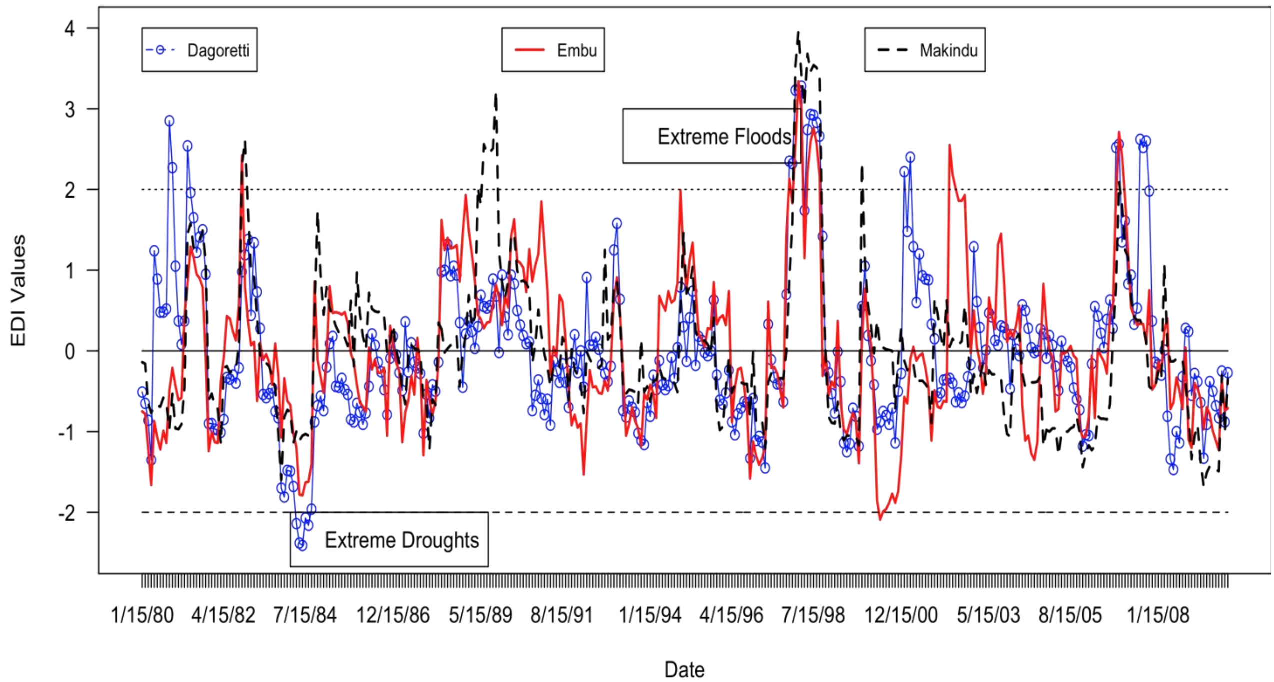


Figure 6-5: Annua1 EDI Variation for Dagoretti, Embu and Makindu

6.4 Mapping Onset, Severity, Duration and Cessation

In the following sections, EDI values for Dagoretti, Embu and Makindu are used to illustrate how EDI can be used to determine (in absolute terms) the onset, severity, duration and cessation of droughts/floods. Owing to its location, Kakamega is affected differently El Niño/La Nina. For instance, the 97/98 floods that were triggered by El Niño did not have devastating effects in Kakamega as the ones witnessed in the other three stations (Karanja 2000).

6.4.1 **The 1983-1985 Drought**

To be able to analyse the 1983-1985 drought, monthly precipitation, EDI and AWRI values were plotted using data for 1982 to 1986.

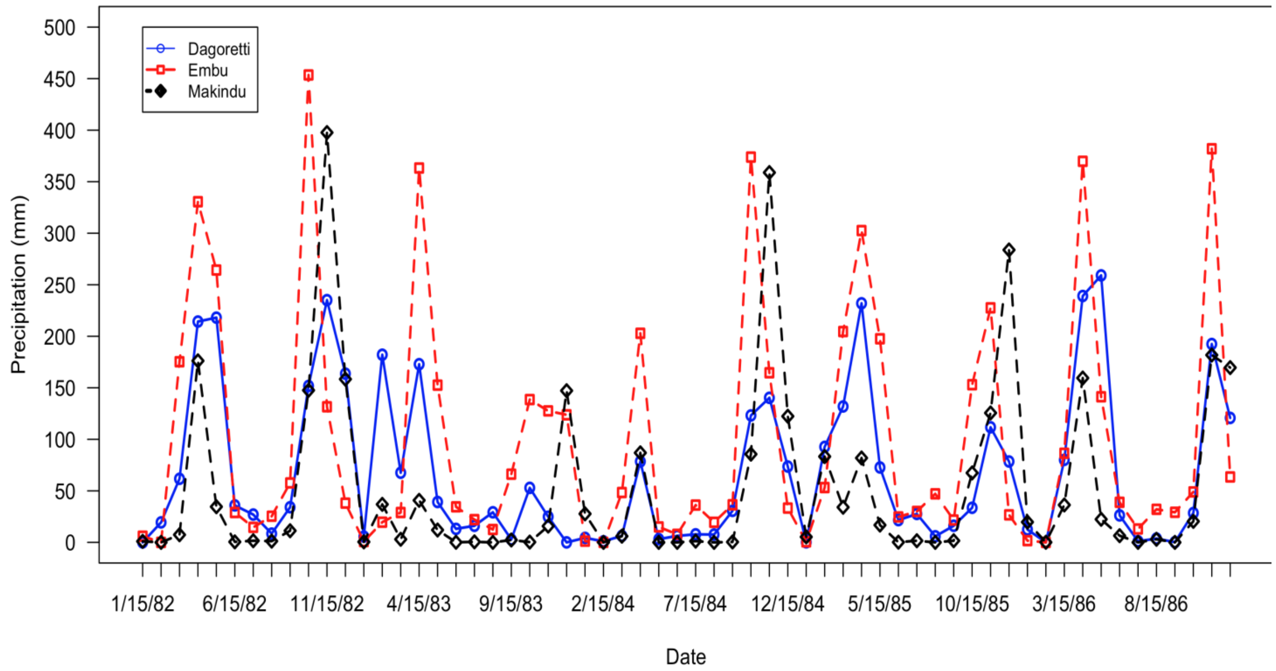


Figure 6-6: Annua1 Precipitation Variation the 1983-1985 Drought

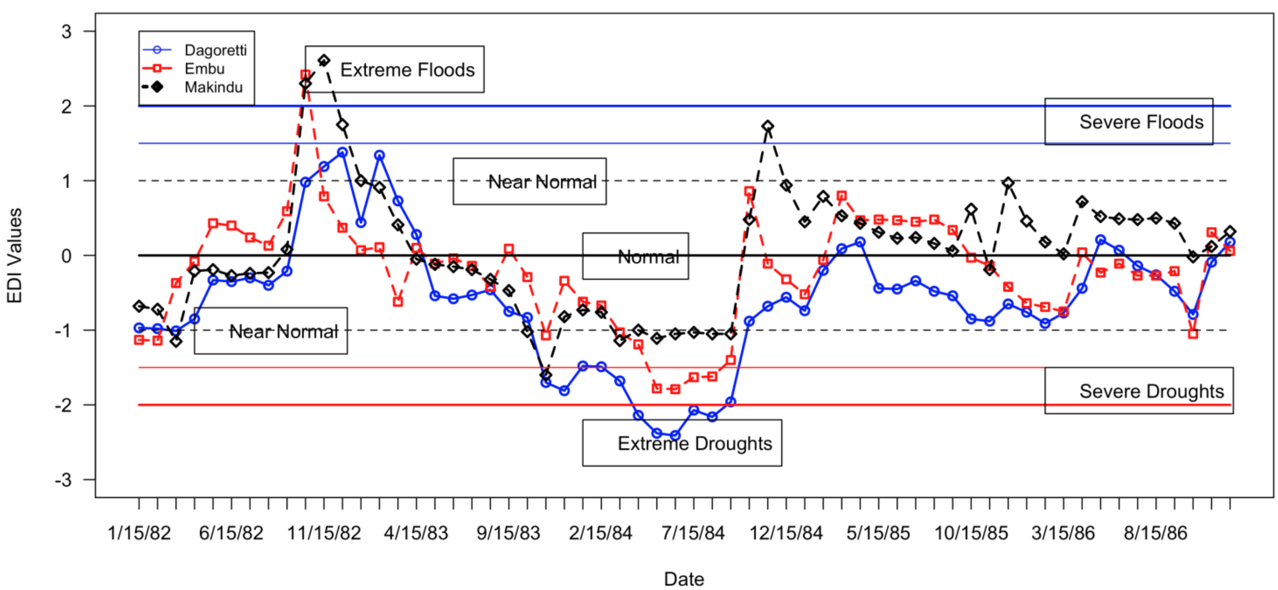


Figure 6-7: Annua1 EDI Variation for 1983-1985 Drought

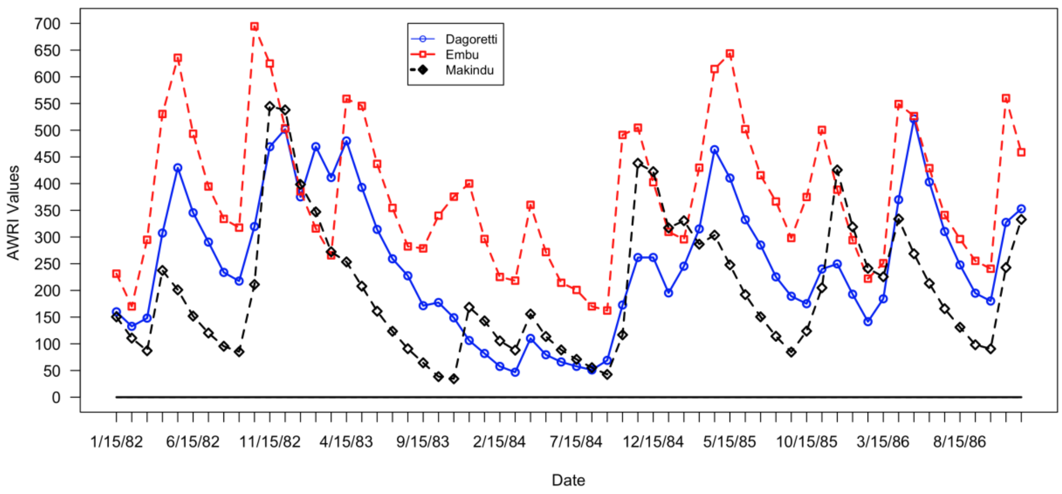


Figure 6-8: Annua1 AWRI Variation for 1983-1985 Drought

From the graphs above, it is evident that the extreme drought started around **April 1983** and ended around **November 1984**. To further map the **onset**, **duration**, **severity** and cessation of this drought, the daily Precipitation, AWRI and EDI were analysed as follows:

The near-normal rains that were received during the **October-November-December, 1984** made the drought improve (but not end) from the extreme to severe levels.

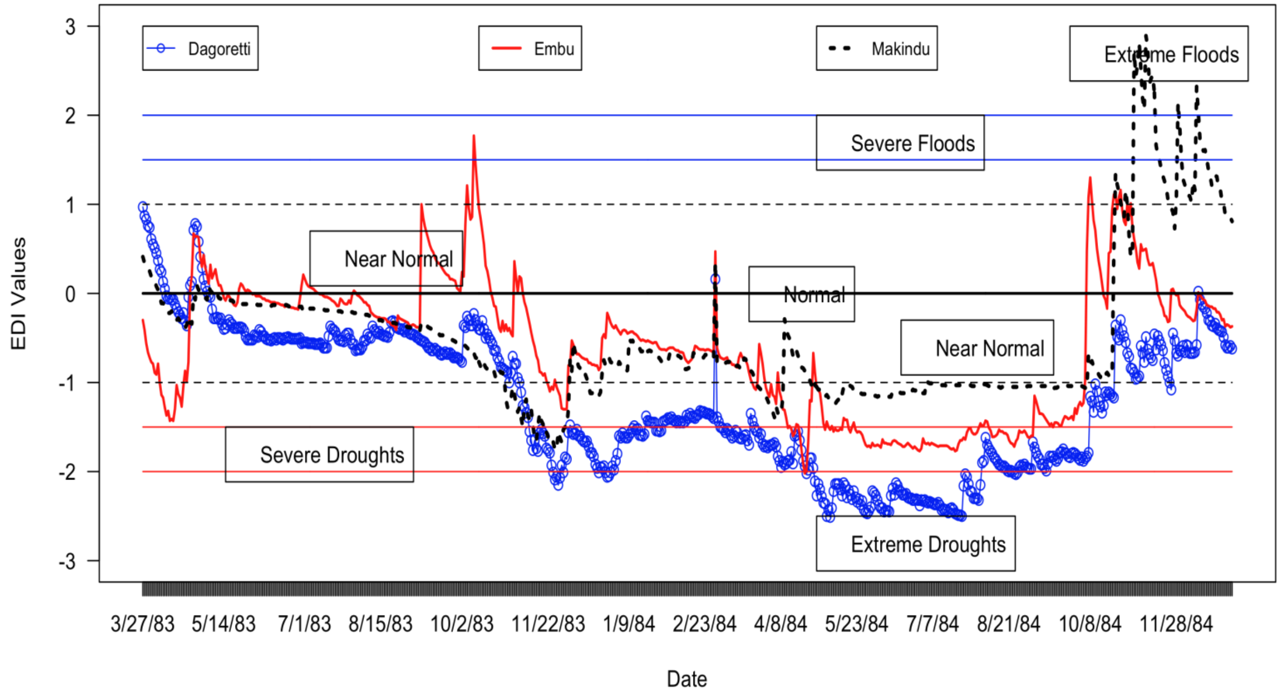


Figure 6-9: Onset, Cessation and Severity of the 1983-1985 Drought

The failure of the March-April-May rains orchestrated the onset of the 1983-1985 drought. The drought was experienced in all the three regions with Dagoretti leading with an average of **-1.2** compared to **-0.6** and **-0.5** for Embu and Makindu respectively). Drought was worse in the ***November 1983 to November 1984*** period. In 1983, the October-November-December rains failed this worsened the already existing drought. On almost a similar date as Dagoretti, (**22 October 1984**), 27.3mm of rainfall was received in Makindu; this brought the **EDI value to 0.47** hence bringing the severe drought to an end too. Ironically, the rains received in Makindu turned out to be excessive; between **21 October 1984** and **27 December 1984**, a total of **560.9mm** was received. The region experienced **flush floods** that reached extreme levels; for instance, a **value of 2.89** was recorded on **10 November 1984**.

 135

Table 6-8: Onset, Cessation and Severity of the 1983-1985 Drought

Event	**Dagoretti**	**Embu**	**Makindu**
Onset	With an EDI value of -0.3, the drought started on 10 April 1983	The drought started on 3 March 1983 recording an EDI value of -0.02	It started later (6 April 1983) where an EDI value of -0.04 was recorded
Duration and Severity	On 31 October 1983, drought reached an EDI value of -1 and by 11 November, the drought became **severe** (-1.55) and eventually reached an **extreme** drought level of -2.01 on 25 November 1983.	Light rains (ranging between 27mm and 69mm) that were received between 20 April and 9 May 1984 temporally normalised the situation. The drought situation re-occurred on 14 May 1984 and worsened when the October-November-December rains failed. On 4 December 1983, the drought reached **severe** levels -1.51) and became **extreme** (-2.02) on 22 April 1984.	The October-November-December had not started as late as 28 October 1983, making the drought reach level -1.19 and a **severe** level of -1.64 on 14 November 1983. Very light rains (totalling 190.7mm) received between 17 November 1983 and 9 January 1984 kept the drought for Makindu slightly above the **extreme** (>=-2) levels; -1.76 is the lowest value of EDI that was recorded here.
Cessation	A total of 38.7mm of rainfall received on 23rd October 1984 brought the EDI level to -0.36.	On 29 September 1984, light rains started (8.1mm for a start). On 6 October 1984, 58.8mm of rainfall raised the EDI to 0.48 and therefore bringing the severe/extreme drought to an end.	On 22 October 1984, 27.3mm of rainfall was received brought the EDI value to 0.47 hence bringing the severe drought to an end too. The rains received turned out to be excessive; between 21 October 1984 and 27 December 1984, a total of 560.9mm was received. The region experienced flash floods that reached extreme levels.

6.4.2 The 1997-1998 Floods

Here, data for 1996 to 1999 was used to analyse the 1997-1998 floods.

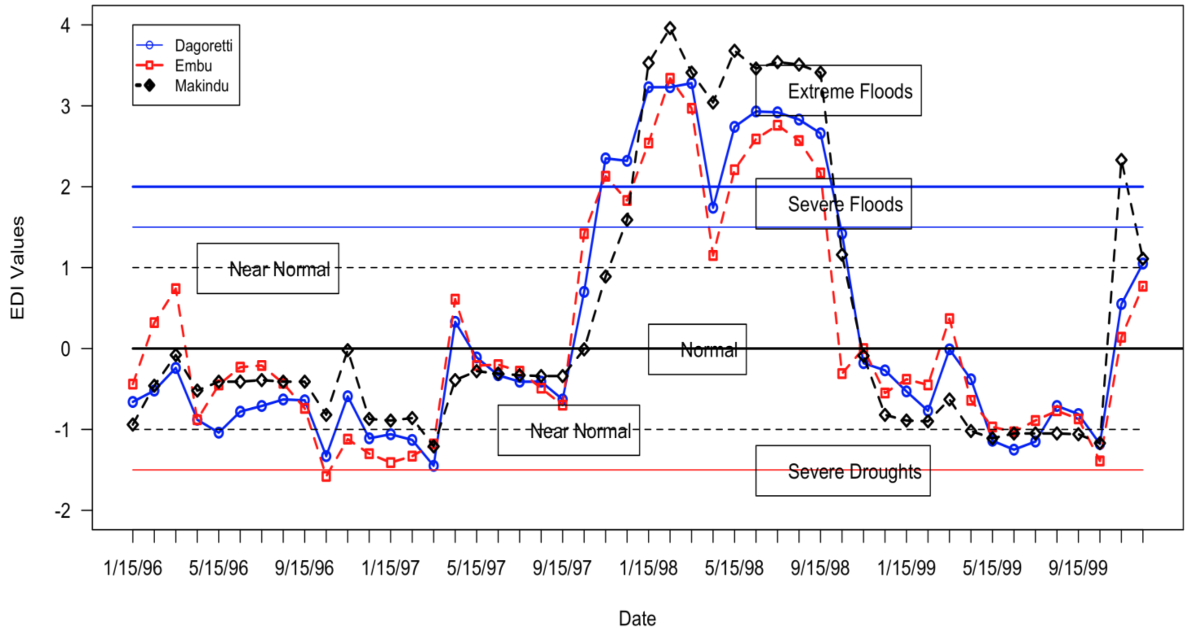


Figure 6-10: Annua1 EDI Variation for 1997-1998 Floods

The graph above point to the fact that the torrential rains received during the October-November-December 1997 rains triggered the extreme floods experienced between **September 1997 and September 1998**. The daily data for this period was further analysed to identity the onset, severity, duration and cessation of the floods as follows:

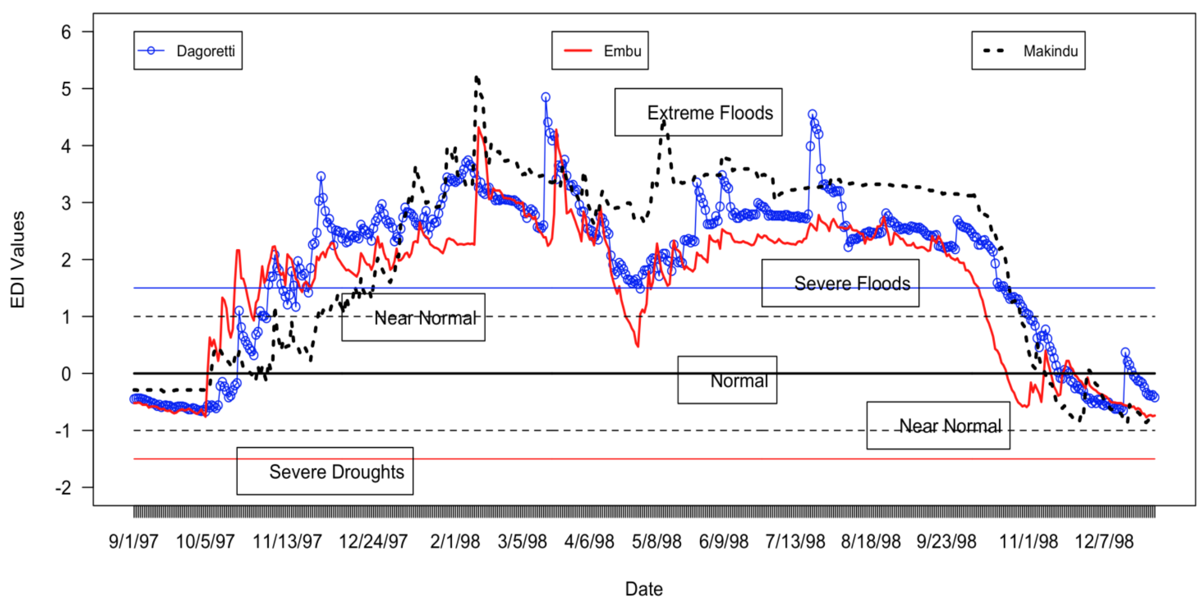


Figure 6-11: Onset, Cessation and Severity of the 1997-1998 Floods

The October-November-December 1997 rains triggered the floods in all the 3 stations. The March-April-May 1998 rains later worsened this. Having received abnormally high amounts of rainfall in the October-November-December rain season, the excess rains during the March-April-May rains season helped to maintain and worsen the already extreme flooding situations in all the three stations. Overall, the floods were worse in Makindu where the mean EDI was **2.1 extreme**). Dagoretti had the second highest levels of flooding with a mean of **1.9** while Embu had a mean of **1.6**. It is also in Makindu where the **highest EDI value of 5.3** was recorded. In 1998, the October-November-December short rains season recorded very low precipitation in all the three stations; this consequently brought the floods to an end.

Table 6-9: Onset, Cessation and Severity of the 1997-1998 Floods

Event	Dagoretti	Embu	Makindu
Onset	On 21 October 1997, 59.6mm of rainfall was recorded shifting the drought situation -0.17) to a flood with an EDI value of 1.1.	The flood started on 13 October after 41.7mm of rainfall leading to an EDI value of 1.33, up from 0.45.	After receiving a total 122.2mm since the onset of the 1997 October-November-December rains, it started flooding on 7th November 1997. On this day alone, a total of 44.8mm of rainfall was recorded raising the EDI value to 1.19.
Duration and Severity	The flood became **severe** (1.56) on 4 November 1997 and eventually **extreme** (2.08) on 7 November 1997. On 29 November, the drought reached an alarming extreme value of 3.46 and remained above 3 from 16 March 1997 to 20 March 1997.	The 63mm of rainfall recorded on 19 October 1997 lead to a **severe** flood of 1.6 and shifted to **extreme** floods 2.16) a day later (20 October 1997) triggered by the 50.6mm of rainfall recorded on this day. An alternating situation of severe and extreme floods remained for most of the period until early October 1998. February is generally a dry month but during this period, lots of rains were received in Embu; for instance, between 11 and 20 February 1998, a total of 164.7mm was recorded; this put the EDI to as high as 4.32 (12 February 998).	Though the flooding subsided for some days, it picked up on 30 November 1997 and eventually reached **severe** levels 1.54) on 15 December 1997. The flood became **extreme** (2.02) on 26 December 1997 and worsened (EDI values of over 3) due to the heavy rains (a total of 429mm) that were recorded in the month of January. More rains pounded in the month of February making EDI reach catastrophic level of 5.27 on 11 February 1998. From February to October 1998, Makindu maintained EDI values within the extreme floods zone.
Cessation	15 November 1998, EDI value of 0.02.	21 October 1998, EDI value of **0.06**..	8 November 1998, EDI value of **0.06**..

6.5 Derived Occurrence Probabilities for Extreme Events

6.5.1 **OND Season Affects the MAM Season**

Using the assumption that there is an interrelation between the two main (October-November-December and March-April-May) rain seasons in Kenya, this section analysis the probability that a drought/flood will occur. This assumption was reached based on the observation that the two extreme events discussed in the earlier sections of this chapter were triggered by the abnormal (failure or excess) of the October-November-December and worsened by abnormal March-April-May rains. In the table below, the OND and MAM seasons are paired up; OND for the previous calendar year and MAM for the following calendar year. Example, the entry 80/81 represents the OND season for 1980 and MAM season for 1981.

Table 6-10: Relationship between OND and MAM Seasons

Year	Dagoretti				Embu				Makindu			
	O-N-D		M-A-M		O-N-D		M-A-M		O-N-D		M-A-M	
	P	EDI	P	EDI	P	EDI	P	EDI	P	EDI	P	EDI
80/81	535	2.1	953	1.4	480	-0.4	899	0.7	176	-0.6	472	0.6
81/82	83	-0.1	494	-0.9	239	-0.7	770	-0.1	186	0.2	218	-0.6
82/83	551	1.2	280	0.2	623	1.2	545	-0.3	704	2.2	56	0.1
83/84	78	-1.3	88	-1.9	390	-0.3	266	-1.2	163	-1.1	93	-1.0
84/85	337	-0.8	437	-0.1	572	0.1	705	0.4	567	0.9	133	0.4
85/86	224	-0.8	578	-0.4	407	-0.1	598	-0.4	477	0.2	218	0.3
86/87	342	-0.2	473	-0.2	495	-0.2	430	-0.6	372	0.2	149	-0.3
87/88	191	-0.7	763	0.4	362	-0.7	927	0.6	120	-0.7	281	0.1
88/89	254	0.0	603	0.3	779	1.3	580	0.6	339	0.0	387	1.2
89/90	380	0.2	627	0.8	577	0.6	833	1.3	465	1.7	267	1.3
90/91	233	-0.5	495	-0.7	675	1.1	468	0.3	387	0.2	137	-0.3
91/92	340	-0.3	528	0.1	324	-0.6	545	-0.9	289	-0.2	189	-0.3
92/93	283	-0.3	149	0.0	475	-0.4	324	0.0	383	0.3	19	0.0
93/94	255	-1.0	420	-0.4	419	-0.8	724	0.1	276	-0.4	170	-0.3
94/95	401	0.5	488	0.3	738	1.4	590	0.8	564	0.4	127	0.5
95/96	245	-0.2	324	-0.6	597	0.4	450	-0.1	180	-0.5	180	-0.3
96/97	169	-0.9	561	-0.5	257	-1.3	675	-0.4	198	-0.5	206	-0.6
97/98	736	1.4	765	2.6	944	1.5	763	2.2	595	0.7	248	3.3
98/99	133	0.6	385	-0.5	278	0.0	463	-0.4	143	0.4	136	-0.9
99/00	493	0.0	268	-0.6	624	-0.4	101	-1.2	590	0.5	140	0.2
00/01	298	-0.7	547	1.4	300	-1.6	608	-0.1	365	-0.3	152	-0.2
01/02	208	0.1	438	-0.3	364	-0.7	1113	1.0	427	0.3	200	0.2
02/03	500	0.0	509	0.0	465	0.7	698	-0.3	257	-0.1	179	-0.3
03/04	256	0.0	597	0.4	471	0.5	360	-0.2	133	-0.7	118	-0.2
04/05	315	0.1	469	-0.2	661	0.2	508	-0.5	149	-0.7	125	-1.1
05/06	160	-0.7	713	0.3	303	-0.6	632	-0.1	92	-1.0	169	-1.0
06/07	675	1.3	423	0.8	962	1.1	511	0.8	673	0.4	102	0.8
07/08	171	1.1	265	-0.7	458	-0.1	516	-0.1	255	-0.4	237	0.2
08/09	287	0.2	275	-0.9	325	-0.5	446	-0.7	103	-0.6	53	-1.4

Key: O-N-D – October-November-December rain season; MAM – March-April-May rain season; P – Precipitation; EDI – Effective Drought Index; AWRI – Available Water Resource Index

6.5.2 EDI Seasonal Interrelationships

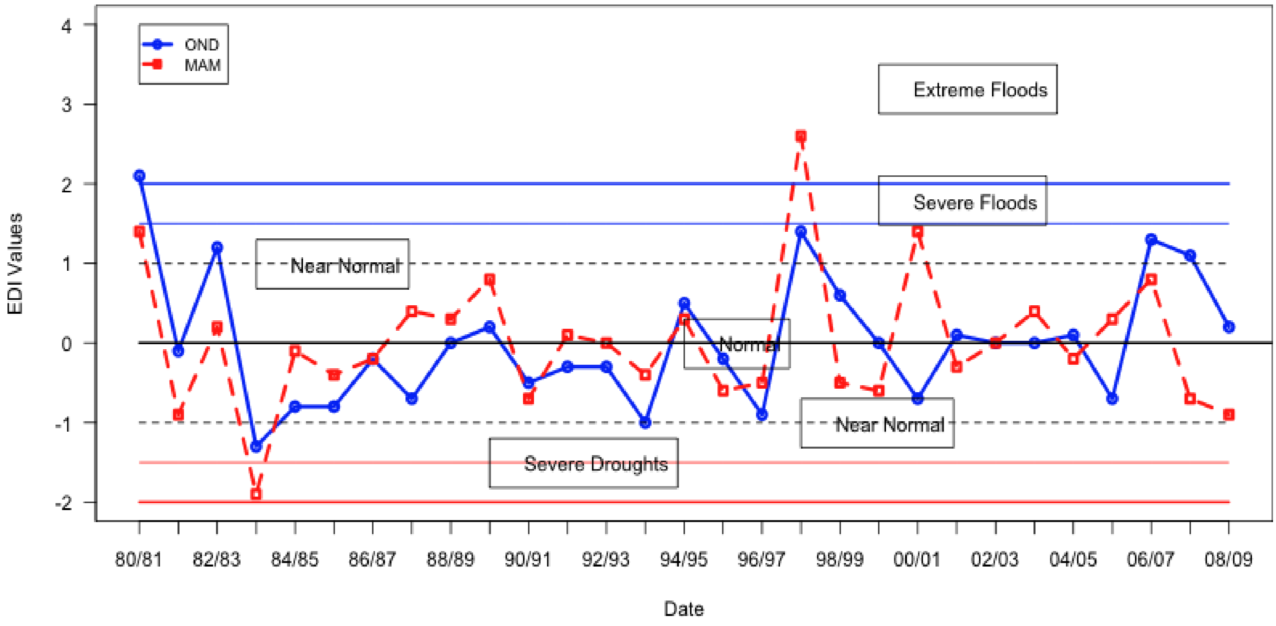


Figure 6-12: Mapping EDI Relationship between OND and MAM Seasons in Dagoretti

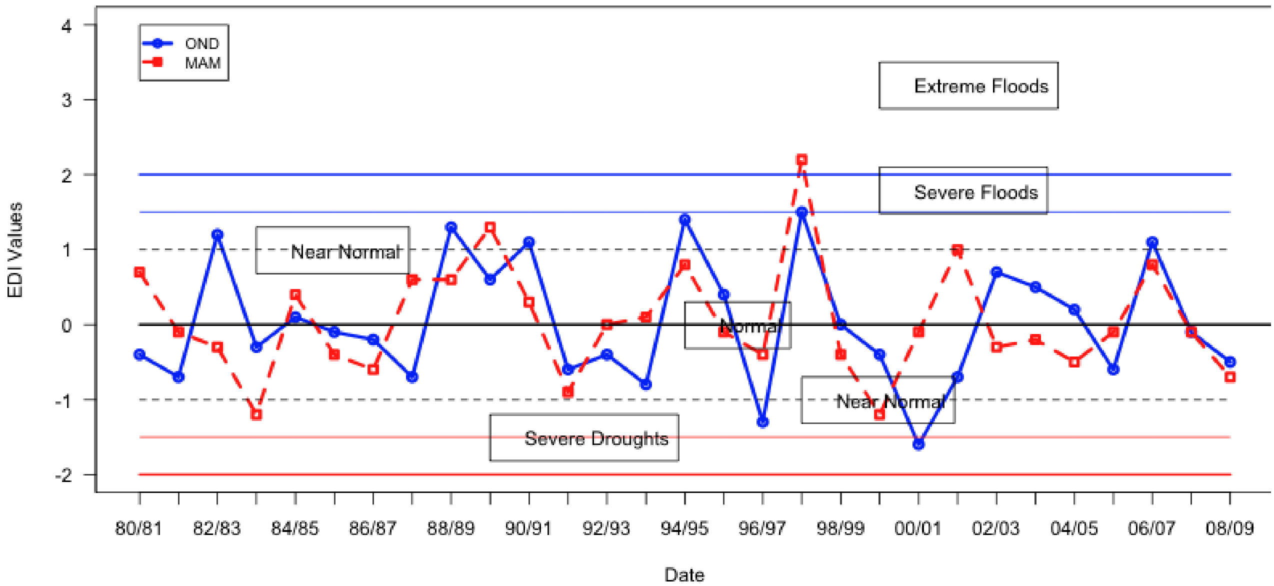


Figure 6-13: Mapping EDI Relationship between OND and MAM Seasons in Embu

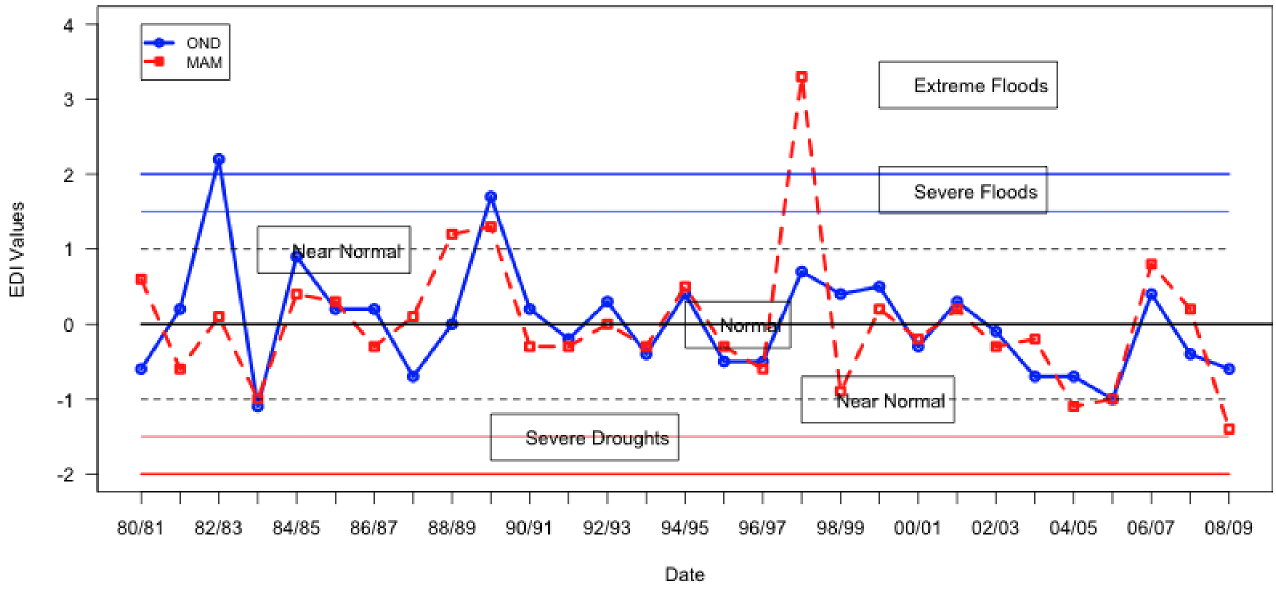


Figure 6-14: Mapping EDI Relationship between OND and MAM Seasons in Makindu

So, does the occurrence of an extreme drought or floods in the OND Season mean a similar event for the following MAM season? Based on the computations on Table 6-10, the following can be deduced:

1983-1984 Drought: The drought experienced during the OND, 1983 season, became worse during the MAM, 1984 season for both Dagoretti (-1.3 to -1.9) and Embu (-0.3 to -1.2). The drought remained almost the same for Makindu (-1.1 to -1.0).

1997-1998 Floods: similarly, the floods experienced during the OND, 1997 season worsened during the MAM, 1998 season in all the three stations. 1.4 to 2.6 for Dagoretti, 1.5 to 2.2 for Embu and 0.7 to 3.3 for Makindu.

Though more tests (using other weather stations and extreme events) may be required, these preliminary results indicate that ***when there is an extreme event (over 2.0 for floods and less than -2.0 for droughts) during the OND rains season, chances that the situation will worsen during the MAM rain season are very high.*** Having said this however, this deduction requires further mathematical analysis to quantify and qualify the correlation. This must be done in due regard of the meteorological factors (such as Sea Surface Temperatures (SSTs)) that are known to influence the rain seasons.

6.5.3 Precipitation Seasonal Interrelationships

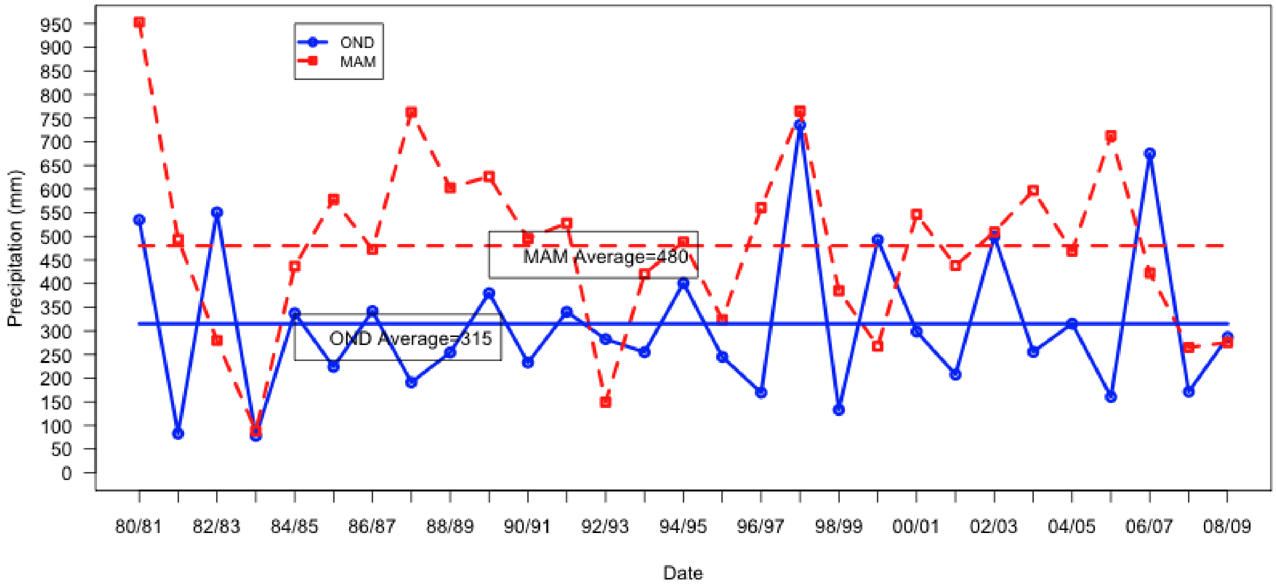


Figure 6-15: Mapping Precipitation Relationship between OND and MAM Seasons in Dagoretti

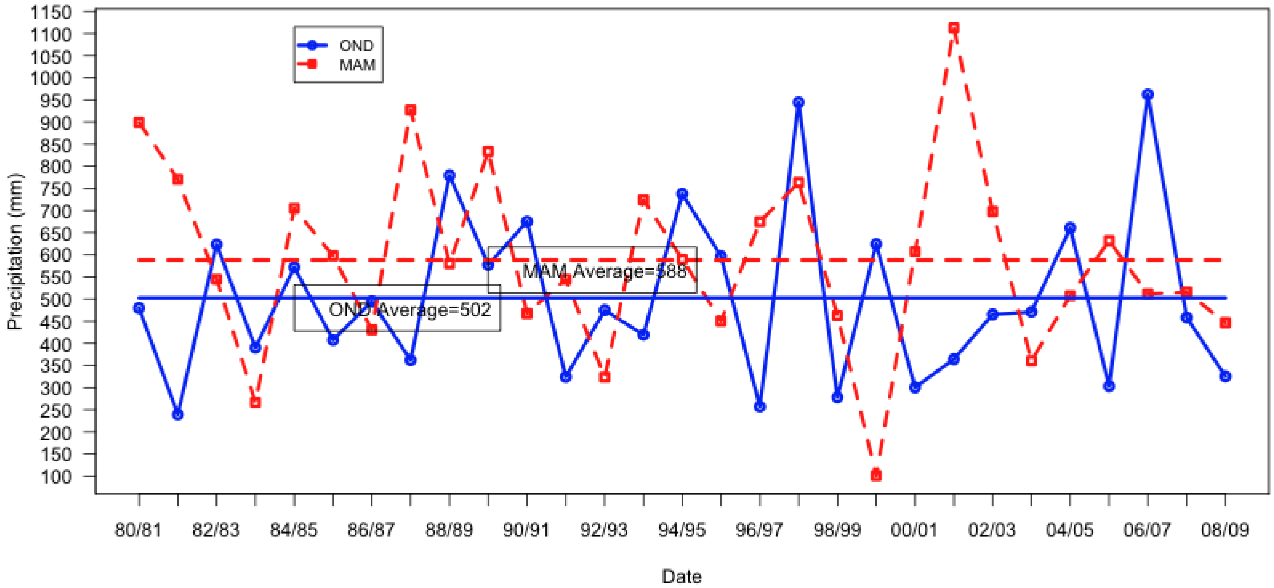


Figure 6-16: Mapping Precipitation Relationship between OND and MAM Seasons in Embu

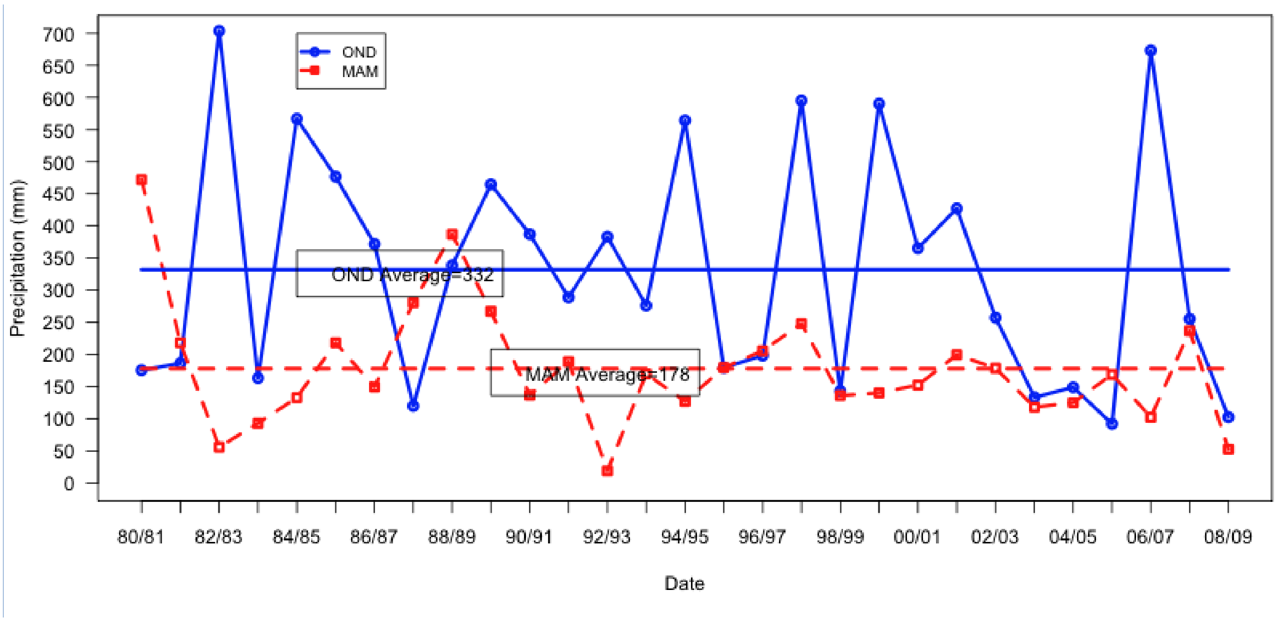


Figure 6-17: Mapping Precipitation Relationship between OND and MAM Seasons in Makindu

Unlike the plots based on EDI (figures 6-12, 6-13 and 6-14), looking at the three precipitation graphs (figures 6-15, 6-17 and 6-18) above one cannot easily detect clear interrelations between the OND and MAM seasons. This further demonstrates the power of EDI in detecting probabilities of extreme events' occurrence.

6.6 Enhancing Decision-Making Using EDI

Data for 2008 to 2009 was used to demonstrate the ability of EDI to complement decision-making. The decision to use this data set was based on the fact that the various forecasts by KMD for this period were readily available from KMD's website (http://www.meteo.go.ke/obsv/agro.html). In particular, SCFs and Dekad reports for this period were used.

6.6.1 **Seasonal Climate Forecasts**

This was illustrated using the **October-November-December 2008 Seasonal Forecasts** and **March-April-May, 2009 SFCs**. The SCFs are usually very detailed reports containing among other sections: (1) summary of the weather of the previous season: (2) forecast for the following season; (3) advice targeted to the various economic sectors based on the anticipated forecast.

i. October-November-December 2008 SFCs

Highlights:

Several locations within the Western Highlands (Kitale, Eldoret, Kakamega) and the Coastal Strip (Mombasa, Malindi, Lamu) received normal to slightly enhanced rainfall in June-July-August (JJA) 2008. Cool and cloudy conditions prevailed in the Central Highlands(Embu, Meru, Nyeri) and Nairobi area particularly from June and extended almost to the end of August. Generally dry conditions prevailed over the rest of the country. The Climate outlook for the "Short Rains" Season (October-November-December: OND) 2008, indicates that Western, Nyanza, and much of the Rift Valley provinces including Central Province and Nairobi area; the Central and Southern parts of Eastern Province (Embu, Meru, Machakos, Kitui, Makueni, Mwingi, etc.) and the southern Coastal strip (Malindi, Mombasa, Kwale, Vanga, etc.) are likely to experience slightly enhanced rainfall (near-normal tending to above-normal). Elsewhere, the seasonal rainfall is expected to be slightly depressed.

EDI Complement

By looking at the EDI, Precipitation and AWRI graph shown below (21 months prior to the SFC above), the phrase "…*likely to experience slightly enhanced rainfall (near-normal tending to above-normal*)…" in the SFC could have been more enhanced if KMD had had access to such information. As the forecast was being issued, it is evident that the drought situation was already serious with Makindu experiencing some instance of severe drought. With the kind of rainfall forecast ('near-normal tending to above-normal'), the farmers and indeed other stakeholders needed to be alerted that the drought was likely to continue.

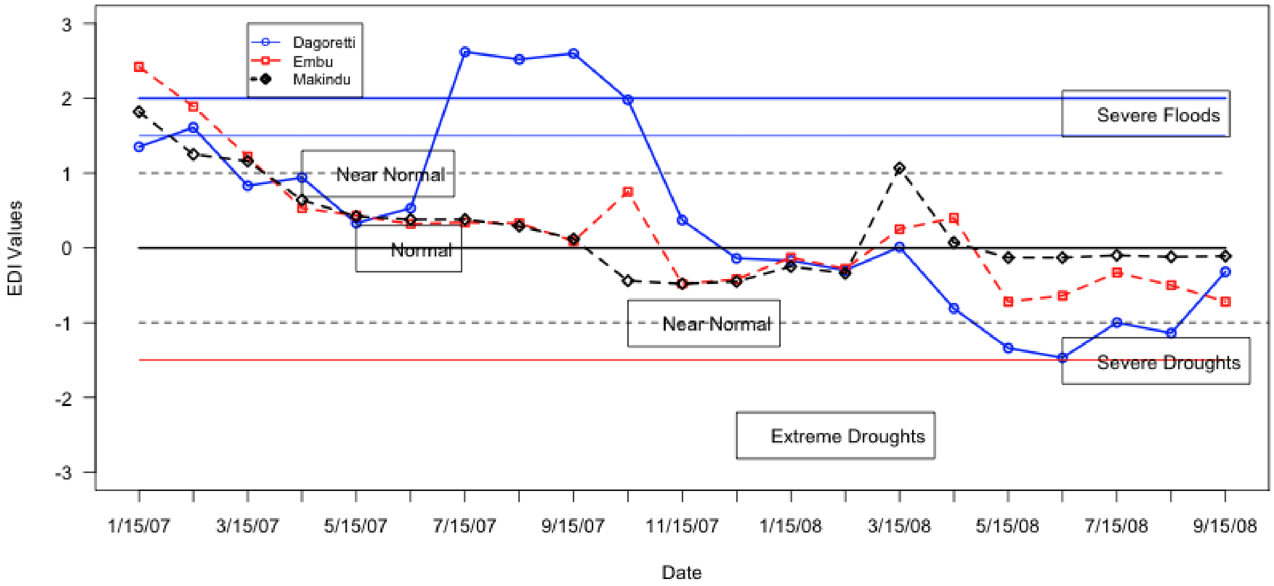


Figure 6-18: The 2007-2009 EDI Graph

ii. March-April-May, 2009 SFCs

Highlights

The March-April-May 2009 seasonal rainfall forecast indicates that most parts of the country are likely to be depressed, except in Western, Nyanza, parts of Rift Valley and Coast Provinces; Sporadic heavy and short-lived rainfall storms may, however, occur in the arid and semi arid lands (ASALS); The rainfall onset is expected to start between the second and third week of March 2009 in Western Kenya and then progress eastward within the season. The October-November-December (OND) 2008 "Short-rains" seasonal rainfall was characterised by very poor temporal distribution. Most parts of the country experienced generally sunny and dry conditions and slightly higher than average daytime temperatures during January-February 2009.

EDI Complement

As in the case for OND, 2008 SFCs, there is no direct link between the drought that was being experienced and meagre rains forecasted for MAM, 2009. This again would have been possible had EDI and AWRI graphs been utilised. Below is such graphs plotted using **daily data for five months from October 2008 to February 2009**, coinciding with the time the MAM, 2009 SCFs were issued. As the graph (below) shows, the little rains received during the OND, 2008 rains did nothing to avert the drought that was already being experienced before their (OND, 2008 rains) onset. Again this affirms the fact that EDI can complement SFCs and aid in guided and informed decisions.

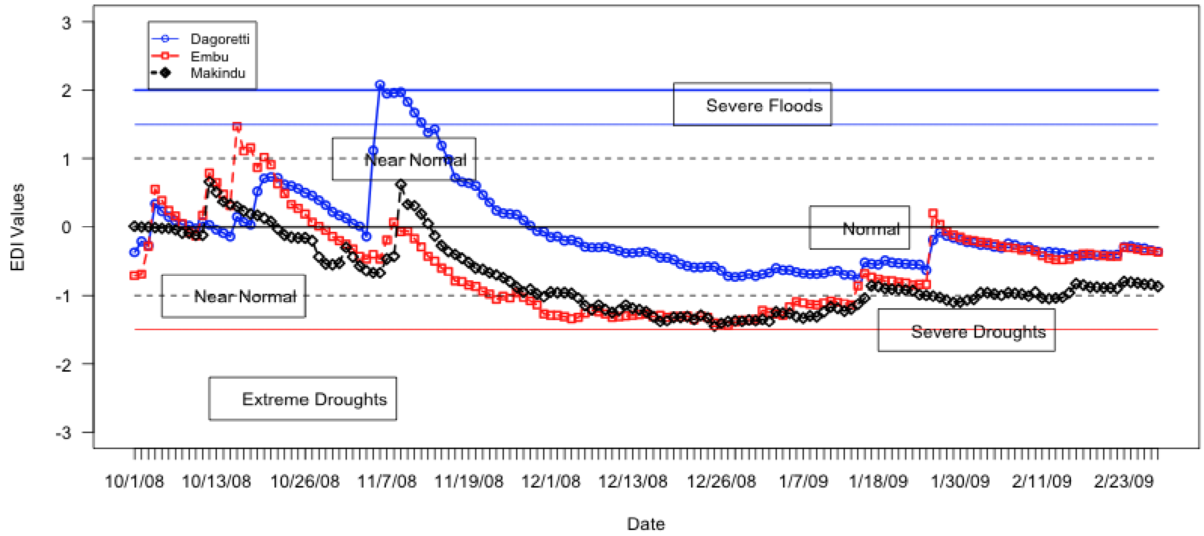


Figure 6-19: The Oct2008 to Feb2009 EDI Graph

6.6.2 Dekadal Reports

Here, two reports were used; the 2nd Dekad, 11 to 20 January 2009 and 14th Dekad, 10 to 20 May, 2009

i. 2nd Dekad, 11 to 20 January 2009

Past 10 Days' Highlights

- *Light to moderate rainfall was experienced over the Central Highlands, Nairobi Area and its environs, South Eastern lowlands for two days i.e. 15th and 16th January 2009; with Embu receiving 40mm, Makindu 29.3mm and Dagoretti 19mm.*
- *In pastoral regions and game parks of Northern Rift Valley, Southern Rift Valley, North Eastern and South Eastern, dry and sunny conditions prevailed resulting in acute water shortages for both human and animal use. Death of livestock has been reported in several regions due to the current drought and pastoralists are being advised to sell some of their livestock to avoid total loss.*

Next 10 Days' Highlights

- *During the next 10 days (21 - 31 January, 2009), Western, Nyanza and Central Rift Valley regions are expected to experience mainly sunny conditions in most places, with light rainfall over few places. Soils will have low soil moisture* *levels and therefore crops performances are expected to be below normal in terms of dry matter production.*

- *Central Highlands, Nairobi area and its environs, are expected to experience generally sunny and dry conditions in most places with light rains over a few places.*
- *In Eastern Province regions of Embu and Meru districts, bordering Mt Kenya, are expected to experience mainly sunny and dry conditions in most places. Poor crop conditions are expected to continue over the high ground areas, whereas at the low lying areas seasonal crop failure is expected.*
- *The Coastal region is expected to experience light rainfall but generally sunny conditions will prevail during the Dekad. Food insecurity is expected to continue. The prolonged dry spells are expected to deplete pastures and water sources for human, livestock and wildlife use and may lead to death of livestock.*

EDI Complement

The effects of the already on-going drought had taken toll; for Embu and Makindu for instance, the drought level was below -1 between 11th and 14th. The rains received in Embu and Dagoretti on 26th brought artificial reprieve but only for a day. Looking at the AWRI graph, the soil moisture was too low to support crops growth. This kind of report would have offered a better decision-making tool than just the decadal report above.

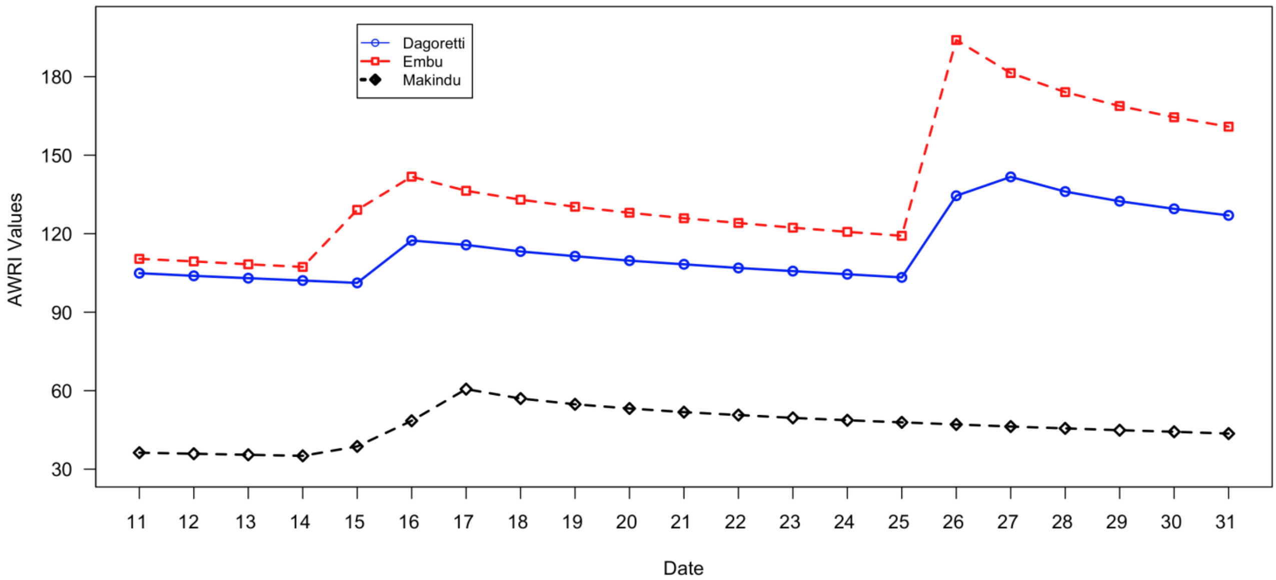


Figure 6-20: Dekad2 and Dekad3 AWRI Graph

ii. **14th Dekad, 10 to 20 May 2009**

(Full detailed report in the ***Appendix 11-3***)

Past 10 Days Highlights

- *During the 13th Dekad i.e. 11 – 20 May 2009, most parts of the country experienced some rainfall;*
- *Central Province, areas bordering Mt Kenya, Nairobi Area and its environs experienced moderate rainfall with the following Dekadal totals; Embu-38.6mm, and Dagoretti-66.5mm.*
- *The current Long Rains has brought about improvements in both fodder for animals and hence an increase in milk production and also availability of fresh vegetables to many households.*

Next 10 Days' Highlights

- *During the next 10 days (21 – 31 May) Western, Nyanza and Central Rift Valley regions are expected to experience moderate to heavy rainfall over several places and crops are expected to continue doing well and correspond to normal growth with normal yields being expected. However, excessive rainfall may cause damage to crops especially in the low lying areas, due to water logging.*
- *Central Highlands, Nairobi area and its environs, are expected to experience moderate to heavy rainfall over several places and crops are expected to continue doing well and correspond to normal growth. The beans crop is expected to reach the maturity stages and with normal yields being expected.*
- *In Eastern Province regions of Embu and Meru districts, bordering Mt Kenya, are expected to experience moderate to heavy rainfall in several places and crops are expected to continue doing well and correspond to normal growth. The beans crop is expected to reach the maturity stages and with normal yields being expected.*
- *In South-eastern lowlands, generally sunny conditions with light rains over few places are expected. Poor crop performances are expected due to insufficient rainfall during past Dekad.*
- *The Coastal region is expected to experience moderate to heavy rainfall during the Dekad. Poor crop performance is expected due to insufficient rainfall during early stages.*

EDI Complement

Though graph for precipitation was giving an indication that the drought situation was improving, both EDI and AWRI graphs indicate that drought was still revenging the land. The drought was actually worsening in both Makindu and Embu and the slight improvement in Dagoretti was just temporary.

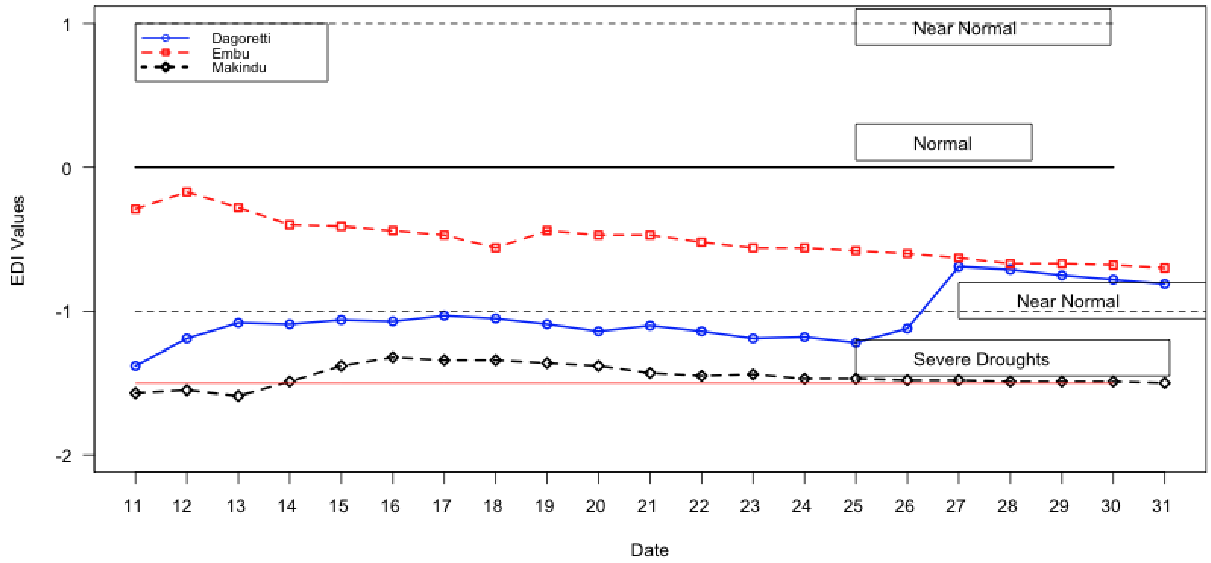


Figure 6-21: Dekad14 and Dekad15 EDI Graph

6.7 Verification and Conclusion

In line with the overall methodology adopted in this research the following section sought to verify the arguments advanced in the sections above using data for Kakamega station.

6.7.1 **Identifying Extreme Events**

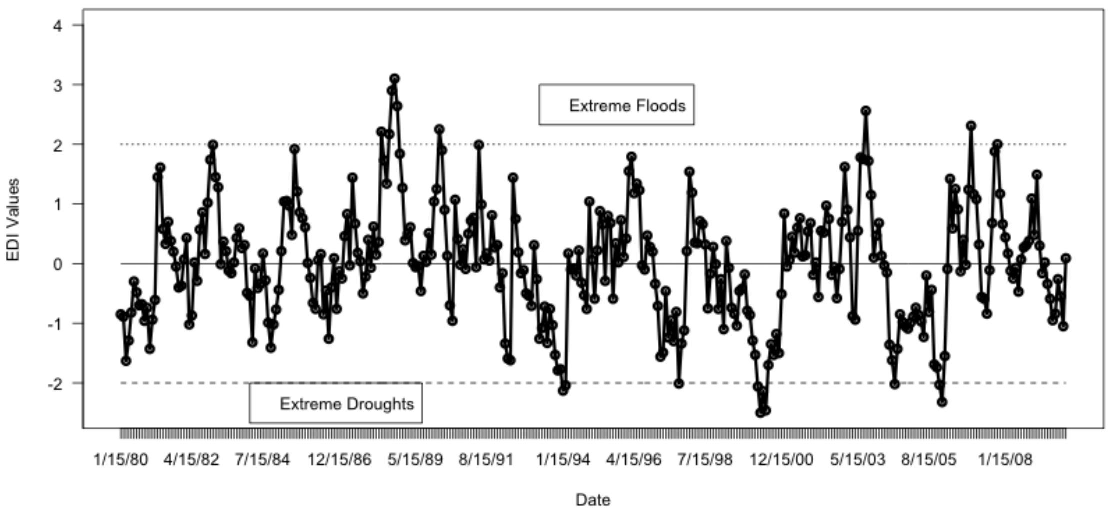


Figure 6-22: Identifying Extreme Events in Kakamega

From above, the following extreme events can be identified:

1988 – 1990 Floods

1992 – 1993 Drought

1997– 2000 Drought

2002 – 2003 Floods

2005 – 2006 Drought

2007 – 2008 Floods

6.7.2 Onset, Severity, Duration and Cessation

The 2007-2009 floods were further analysed to verify that EDI can indeed be used to determine the onset, severity, duration and onset of droughts/floods

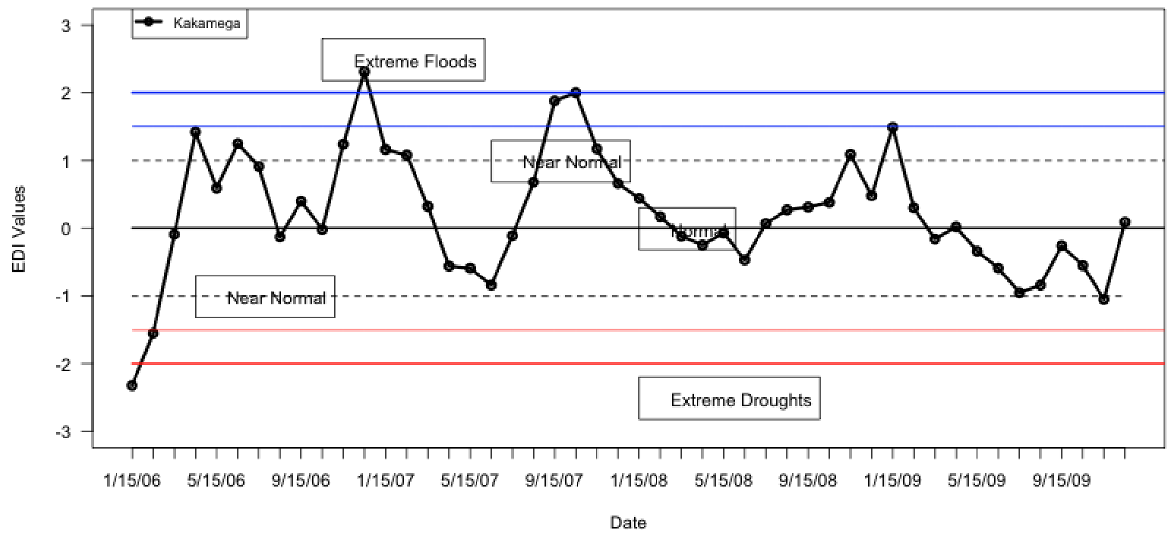


Figure 6-23: The EDI Values showing the 2007-2008 Floods in Kakamega

The longest floods started in November 2007 and plotting the daily EDI values for this period results in:

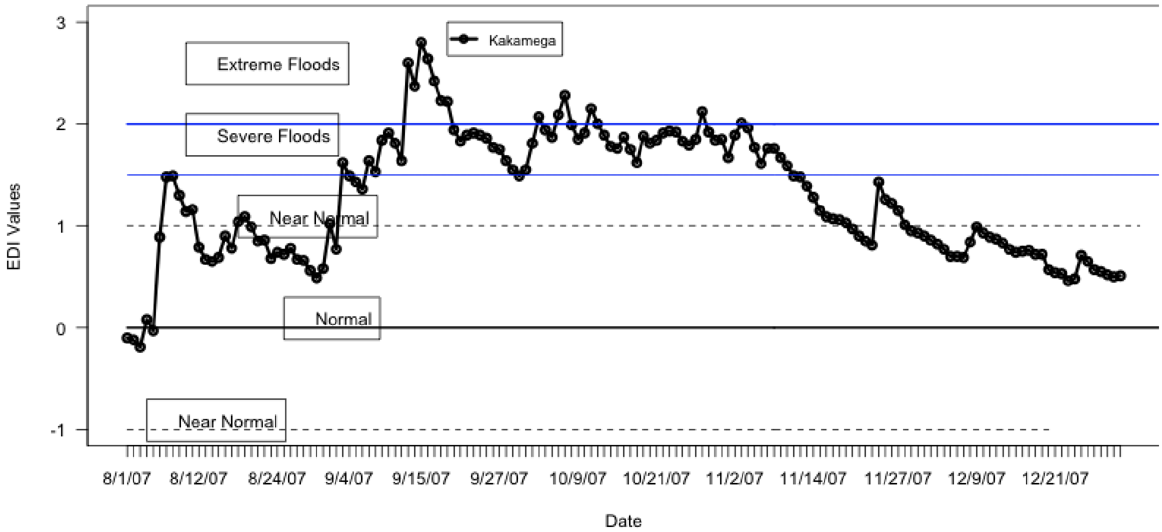


Figure 6-24: The 2007-2008 Floods in Kakamega [Onset, Severity and Cessation]

Onset: On 6 August 2007, 63.1mm of rainfall received raised EDI from -0.03 to 0.89 and when on the following day (**7 August**) another 51.9mm was received, it flooded raising **EDI to 1.48** (very close to severe floods).

Duration and Severity: The rains subsided hence reversing the flooding situation until 3 September 2007 when 64.3mm of rainfall was recorded. Since the grounds were still wet (EDI of 0.77) these rains led to severe drought of 1.62. The floods remained severe until 13 September when they worsened to **Extreme Floods at an EDI value of 2.1**. The worst flooding (**EDI of 2.8**) during this period was recorded on 15 September. On this day, 42.7mm of rainfall was recorded, raising the AWRI value 518.1. The flood remained between severe and extreme levels until 13 November.

Cessation: There were no rains falling in Kakamega between 25 November and 6 December and this dried up the grounds; this brought the short-lived floods to an end on 1 December 1997.

7. Drought Forecasting using Artificial Neural Networks

"There is a tendency among users to throw a problem blindly at a neural network in the hope that it will formulate an acceptable solution…" However, " it is vital to adopt a systematic approach in the development of ANN models, taking into account factors such as data pre-processing, the determination of adequate model inputs and a suitable network architecture, parameter estimation optimisation) and model validation (Maier, Graeme 2000, *page 1).*

*Throughout human history, departures from the seasonal rhythms of climate often provided the difference between wealth and poverty, feast and famine, health and disease, and even life and death. (*Stern, William 1999) page *(ix)*

7.0 Introduction

Like Chapter 6, this chapter also discusses the implementation Component 2 of the Integrated DEWS Framework; that is, ***Drought Monitoring and Prediction'***. In particular, it deals with the 'Prediction' element. First, historical daily weather data for four weather stations in Kenya is used to train Artificial Neural Networks which are in turn used to forecast droughts for short, medium and long term. Though the well-developed drought indices such as SPI, PDSI and EDI perform very well in mapping droughts in spatial and timescale dimensions, they only detect the events already happening (Morid, Vladimir et al. 2007). The main focus of the current research is to build an effective early warning system for droughts and as such, forecasting/predicting future droughts is crucial. The latter is the role of Artificial Neural Networks (ANNs) as described in this chapter.

El Nino–Southern Oscillation (ENSO) and North Atlantic Oscillation (NAO) are the most developed and most commonly used medium-term drought forecasting indices (Trenberth, Branstator et al. 1998). One of the drawbacks of these two indices however is the fact that they do not forecast the severity of the predicted drought (Morid, Vladimir et al. 2007). The use of ANNs to forecast future values of EDI and AWRI attempts to address this drawback as well as introduces a new addition, forecasting daily drought indices. Though invented in 1943 (McCulloch, Pitts 1943), it is the coming-on-stage of the Back-Propagation training algorithm for feed-forward ANNs in 1986 (Rumelhart, Hinton et al. 1986) that boosted the application of ANNs in several real-life application areas such as drought forecasting.

Maier, Graeme (2000) described five key considerations to successful implementation of ANNs as:

a) ***ANNs' performance evaluation criteria***: how will the performance of the model be judged? The relevant criterion for this study was 'accuracy of predicted results'. This also happens to be the most commonly used criterion (Demuth, Mark et al. 2009).

b) ***Data set division criteria***; deals with how to share the available dataset among the ***training***, ***validation*** and ***testing*** phases of ANNs. By default, tools such as MATLAB Neural Network Toolkit adopt ***70:15:15*** percentages respectively (Demuth, Mark et al. 2009). This data set division criterion was adopted in this research.

c) ***Data pre-processing*** with the aim of ensuring some form of ***standardisation***. In the current research, all rainfall data was first subjected to EDI computation (as explained in the previous chapter) and hence, it was already ***standardised***/***homogenisation***. Further, the ***mapminmax*** function implemented in the MATLAB Neural Network Toolkit was applied. The latter puts all the input values into [-1:1] range. This in turn ensured that all variables involved had equal representation during the training.

d) ***Determining model input***, this is purely based on *a priori* knowledge of causal variables in conjunction with inspections of time series plots of potential inputs and outputs. This research involved an array of weather parameters such as daily readings of temperature, rainfall, relative humidity and wind direction. From the rainfall values, both daily and monthly Effective Drought Index (EDI) and Available Water Resource Index (AWRI) were computed and extensively used as inputs/outputs of the neural networks.

e) ***Selecting a suitable network architecture*** which is made up of two aspects:

- The **type of connection** (are there loops?) among the nodes; and
- How many hidden layers and how many nodes in each of the hidden layers. The number at the input and output layers is generally determined by the problem domain.

This is referred to as the geometry of the network.

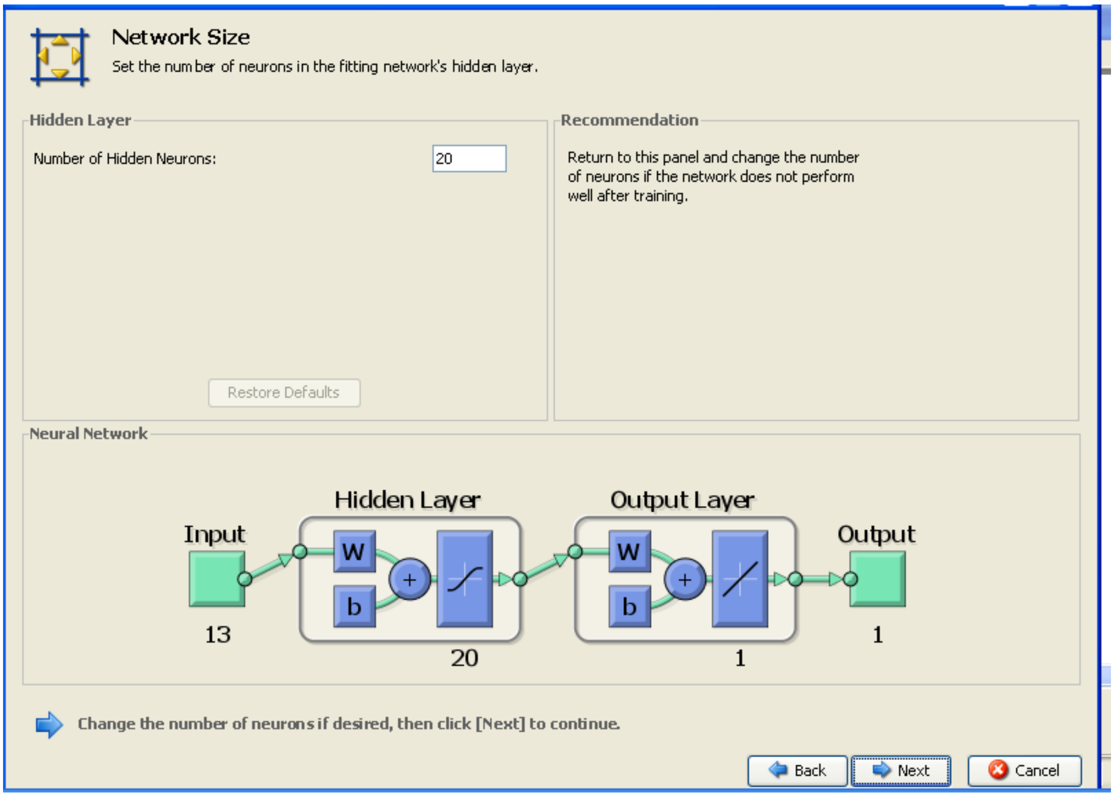


Figure 7-1: Setting Network Size in MATLAB NN-Toolkit

In line with the **Pi**lot, **E**xploratory and **C**onfirmatory **E**xperiment**s** (PiECEs) described in Chapter 3, a series of experiments under Pilot, Exploratory and Confirmatory were followed in developing optimal neural networks to forecast droughts for short lead-times (up to 14 days), medium lead-times (up to eighteen months) and long lead-times (up to four years).

7.1 Pilot Phase

7.1.1 Overview

During this phase, data for 30 years (1980 to 2009) for Embu Weather Station was used to experiment the effects of combing various Inputs and Targets. The Daily EDI output files generated in Chapter 6 (see table 6-7) were used. Using this data, a total of 21 Neural Networks were created, trained, tested and evaluated using MATLAB's implementation of the Peceptron (Demuth, Mark et al. 2009). The following default configurations were adopted:

Data Normalisation: To normalise the input values, default data pre-processing function, ***mapminmax*** that maps the range of input values to the range [-1 1] was used.

Network Architecture: One hidden layer with 20 neurons was selected. During this (pilot) phase, experiments of varying the number of neurons were carried out but the value 20 outperformed them; hence the decision to use the default value 20. For example, during the training of the ANNs for predicting EDI value for Dagoretti for 7-day lead time, the number of hidden layers was varied between 10 and 40 at an interval of 5. The MSE and R values were used to rank them and the network with 20 hidden layers had the best performance.

Data Division Criteria: For each data set, the ratio of 70%:15%:15% for ***training***, ***validation*** and ***testing*** respectively was used.

Network Training: Training was carried out using ***Levenberg-Marquardt backpropagation (trainlm) algorithm***

Graphical Output: Three standard MATLAB charts were plotted: Regression, Performance and Training State. Plotting the Fit was not possible because the Networks had too many inputs (from 6).

Sample Graphical Output

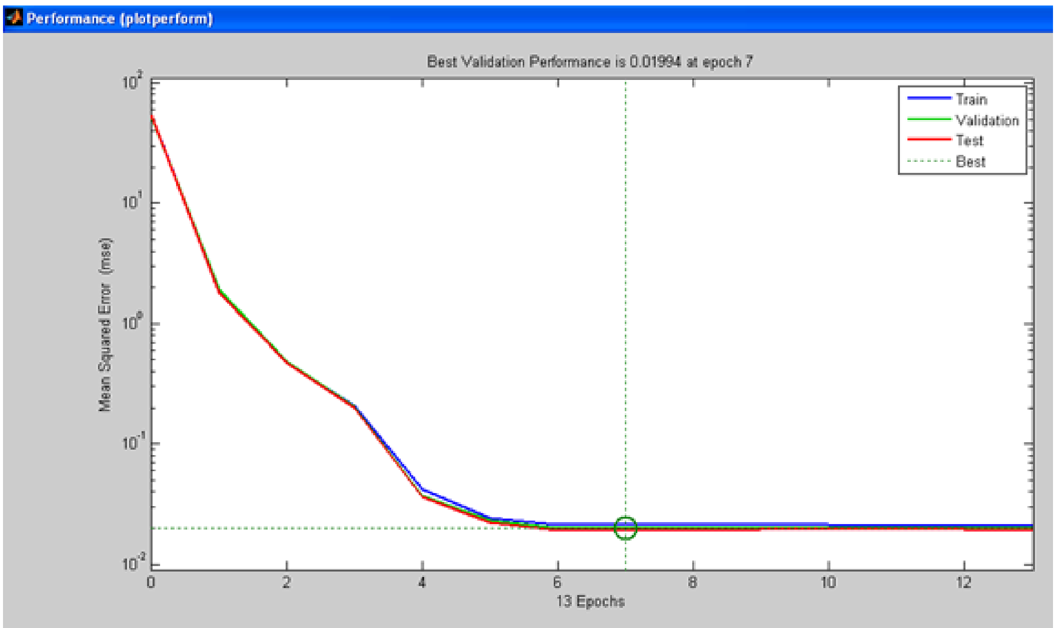


Figure 7-2: Network 14 – Performance Graph

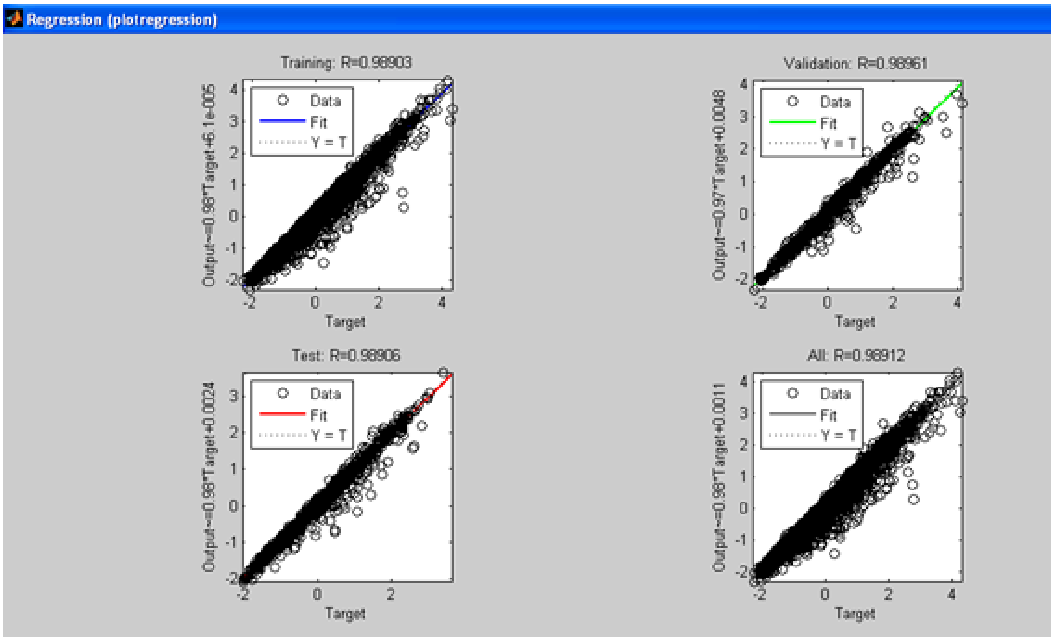


Figure 7-3: Network 14 – Regression Analysis Graph

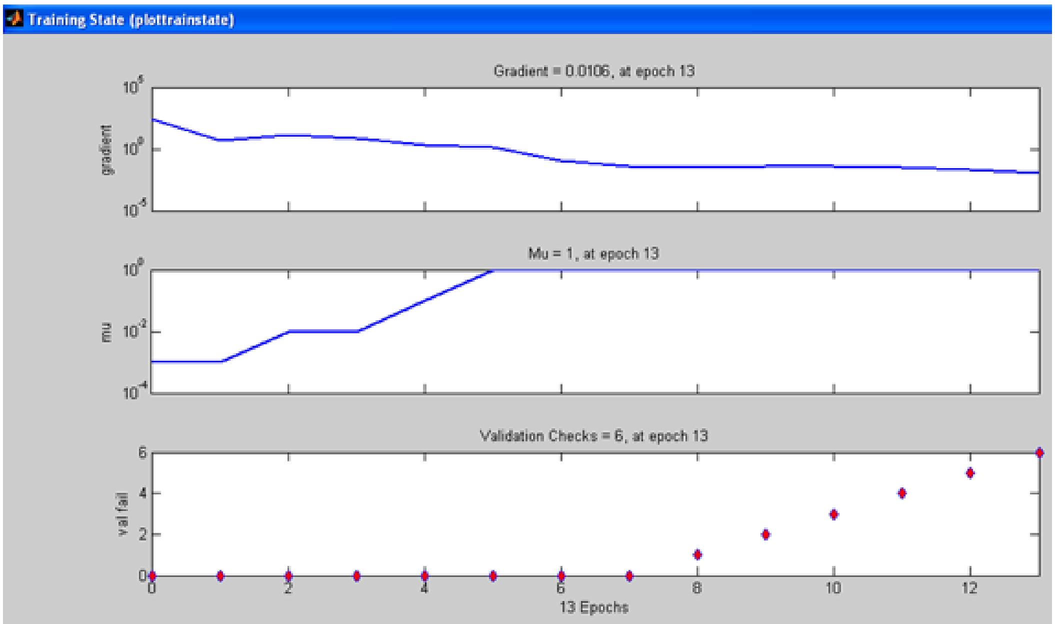


Figure 7-4: Network 14 – Training State Graph

Network Geometry: The Networks in this phase were designed to predict EDI and/or AWRI for the next day given a combination of EDI (E), Precipitation (P) and AWRI (W) for six previous days. The networks were categorised as follows:

- 7 Networks with 2(EDI and AWRI) outputs
- 7 Networks with EDI as the output
- 7 Networks with AWRI as the output

Given that precipitation is itself a function of so many other linear and nonlinear functions, it was not considered as an output in work (Weichert, Gerd 1998). A simple Java program was then created to convert input files to the following inputs-targets mapping.

(i) **Homogeneous inputs, homogeneous output example:**

Network 8: $E_{n+1} = f(E_n, E_{n-1}, E_{n-2}, E_{n-3}, E_{n-4}, E_{n-5})$:-

Given EDI values for the last 6 days, forecast the EDI value for the next day.

(ii) **Heterogeneous inputs, homogeneous output example:**

Network 14: $E_{n+1} = f\ (P_n, P_{n-1}, P_{n-2}, P_{n-3}, P_{n-4}, P_{n-5})\ (E_n, E_{n-1}, E_{n-2}, E_{n-3}, E_{n-4}, E_{n-5})\ (W_n, W_{n-1}, W_{n-2}, W_{n-3}, W_{n-4}, E_{n-5})$:-

Given Precipitation, EDI and AWRI values for the last 6 days, forecast the EDI value for the next day.

(iii) **Homogeneous inputs, heterogeneous output example:**

Network 2: $E_{n+1}, W_{n+1} = f\ ({}_n, E_{n-1}, E_{n-2}, E_{n-3}, E_{n-4}, E_{n-5})$:-

Given EDI values for the last 6 days, forecast the EDI and AWRI values for the next day.

(iv) **Heterogeneous inputs, heterogeneous output example:**

Network7: $E_{n+1}, W_{n+1} = f\ (E_n, E_{n-1}, E_{n-2}, E_{n-3}, E_{n-4}, E_{n-5})\ (W_n, W_{n-1}, W_{n-2}, W_{n-3}, W_{n-4}, W_{n-5})\ (P_n, P_{n-1}, P_{n-2}, P_{n-3}, P_{n-4}, P_{n-5})$:-

Given EDI, AWRI and Precipitation values for the last 6 days, forecast the EDI and AWRI values the next day.

Table 7-1: Performance of the Pilot Phase Neural Networks

Network	I			T		Mean Square Error (MSE)				Regression (R)			
	P	E	W	E	W	Tr	Vl	Ts	Rn	Tr	Vl	Ts	Rn
Category I: Two outputs (EDI and AWRI)													
Network1	Y	N	N	Y	Y	2,340.90	2,358.28	2,358.05	7	0.58	0.68	0.62	7
Network2	N	Y	N	Y	Y	1,169.10	1,365.17	1,287.50	4	0.94	0.94	0.95	6
Network3	N	N	Y	Y	Y	41.24	40.19	47.63	5	0.76	0.77	0.75	3
Network4	Y	Y	N	Y	Y	795.01	861.62	885.25	3	0.96	0.96	0.96	5
Network5	N	Y	Y	Y	Y	43.00	32.74	42.15	2	0.97	0.98	0.97	1
Network6	Y	N	Y	Y	Y	39.45	51.13	50.33	6	0.76	0.76	0.74	4
Network7	Y	Y	Y	Y	Y	35.66	59.27	45.75	1	0.97	0.97	0.97	1
Category II: Output EDI only													
Network8	Y	N	N	Y	N	0.84	0.82	0.85	7	0.36	0.32	0.32	7
Network9	N	Y	N	Y	N	0.02	0.03	0.02	4	0.99	0.99	0.99	1
Network10	N	N	Y	Y	N	0.38	0.35	0.38	6	0.78	0.78	0.78	6
Network11	Y	Y	N	Y	N	0.02	0.02	0.02	2	0.99	1.00	0.99	1
Network12	N	Y	Y	Y	N	0.02	0.02	0.02	3	0.99	0.99	0.99	1
Network13	Y	N	Y	Y	N	0.31	0.31	0.33	5	0.82	0.82	0.82	5
Network14	Y	Y	Y	Y	N	0.02	0.02	0.02	1	0.99	0.99	0.99	1
Category III: Output AWRI only													
Network15	Y	N	N	N	Y	4,672.09	4,847.33	4,743.63	7	0.50	0.50	0.46	7
Network16	N	Y	N	N	Y	2,447.19	2,566.56	2,669.63	6	0.78	0.77	0.77	6
Network17	N	N	Y	N	Y	87.57	77.81	80.48	2	0.99	0.99	0.99	1
Network18	Y	Y	N	N	Y	1,655.01	1,834.05	1,703.69	5	0.85	0.85	0.85	5
Network19	N	Y	Y	N	Y	84.57	91.60	72.05	1	0.99	0.99	0.99	1
Network20	Y	N	Y	N	Y	77.17	78.17	118.44	4	0.99	1.00	0.99	1
Network21	Y	Y	Y	N	Y	80.67	79.87	97.39	3	0.99	0.99	0.99	1

KEY: *P – Precipitation; E – Effective Drought Index; W – Available Water Resource Index (AWRI); Tr – Training; Vl – Validation; Ts – Testing; I- Inputs; T – Targets; Y-yes (included in the input/targets); N – No (Not included in the inputs/targets); Rn-Rank (The Rank of the Network by performance MSE and R); for example, Network7 has the lowest error in the Category 1 while Network14 and Network 19 have the lowest error in Category 2 and 3 respectively)*

Note: though the ranking of the networks was based on the average of the performance MSE and R) of the three data sets (Tr, Vl and Ts); the value of V1 is preferred (and was used in the actual neural networks) because it is the measure of the network's ability to carry out the future forecasting (classify dataset it has not encountered before).

Ranking the performance of the network: The networks in ***Table 7-1*** were ranked using the following criteria:

iv. **Regression Analysis**: the higher the value, the higher the rank because it is the measure of the correlation between the inputs and the outputs.

v. **Mean Square Error**: the smaller the value the better the network; it is the average squared difference between outputs and targets. However, the value was bound to be directly proportional to the size of the outputs values. For example, the outputs/targets for Networks 15 to 21 are those of AWRI whose mean was **194.58** while for Networks 7 to 14 are for EDI values that ranged between **-2.28** to **4.32** (an absolute mean of **±0.76521**). Calculating the mean of the output for Networks1 to 7 was not possible because this is made up of two values (EDI and AWRI) that are in very different scales. In order to get the actual implications of the errors for Networks 8 to 21, the Root Mean Square Error (RMSE) and the Percentage of the RMSE were computed.

In **Network 11** for instance, an MSE of **0.02204** is equivalent to RMSE **0.15** SQRT (0.02204). Given that this Network's output is an EDI (ranges between **-2.28 to 4.32**), this implies a percentage error of **3.7** to **6.58%.** When the network predicts an EDI value of **-2.2**, this has an error of **±0.15,** which is not a significant error. On the other hand, an MSE error of **77.1658** in **Network 20** is equivalent to RMSE of **8.8**. This Network's outputs are AWRI whose average is **194.58**. Consequently, the percentage error of **4.53%** may or may not be significant depending on the use into which the forecast is put.

7.1.2 Selected Networks

An ideal Network would be the one that predicts EDI and/or AWRI given precipitation only, however, these (1, 8 and 15) had the worst performance. Secondly, by selecting a network that uses all the 3 inputs (P, E and W) and gives both EDI and AWRI as outputs is ideal because it ensures that only one network is needed to solve the current problem. This scenario is represented in **Networks 7** which had the best performance in Category I of the networks. What about creating two different networks that use all the three inputs (P, E and W) to predict EDI and AWRI respectively? This is achieved in **Network 14** and **21.** Though Network14 had the best performances in Category II, Network 21 was the third after **Network 19** and **17** in category III.

The networks with average (Rank 1 to 3) performance and that have Precipitation as input were selected for further investigation during the Exploratory Phase. These are Networks 7, 11, 14, 20 and 21. Finally, in order to exhaustively investigate the best networks for building bi-network (two networks, for EDI and AWRI respectively), the two best performing networks in each of these categories were selected.

7.1.3 Omitted Networks

Precipitation alone as input: **Networks 1, 8 and 15** had the worst performance in their respective categories. This proved that using Neural Networks, precipitation alone could not be used to compute EDI and/or AWRI values.

EDI/AWRI to Compute AWRI/EDI: An attempt to use either EDI to compute AWRI and vice versa did not yield desirable results. This is an indication that there is no any form of relationship between the two. This made Networks **2, 3, 10** and **16** give poor performance.

EDI/AWRI and Precipitation to Compute AWRI/EDI: Finally, combing EDI and Precipitation to predict AWRI or AWRI with Precipitation to predict EDI did not work either. This made **Networks 4, 6, 13, and 18** not perform well.

7.2 Exploratory Phase I

Best EDI and AWRI Networks Model

Using data for Embu, Dagoretti and Makindu weather stations, the 10 Neural Networks identified in the Pilot Phase were trained yielding the following results:

Results for Dagoretti Station

Table 7-2: Performance of the Exploratory Phase's Neural Networks - Dagoretti

Network	Mean Square Error				Regression			
	Tr	Vl	Ts	Average	Tr	Vl	Ts	Average
Network5	34.4754	27.7476	38.8559	33.6930	0.98315	0.98450	0.98408	0.98391
Network7	35.1539	35.1539	33.3021	34.5366	0.97997	0.99816	0.98864	0.98892
Network9	0.0188	0.0178	0.0200	0.01887	0.99018	0.99068	0.99001	0.99029
Network11	0.0165	0.0254	0.0149	0.01899	0.99126	0.98751	0.99211	0.99029
Network12	0.0166	0.0199	0.0221	0.0195	0.99138	0.98955	0.98865	0.98986
Network14	0.0174	0.0151	0.0240	0.0188	0.99110	0.99159	0.98793	0.99021
Network17	68.5308	59.6619	72.7853	66.9927	0.99378	0.99442	0.99334	0.99385
Network19	68.4546	81.1977	53.5809	67.7444	0.99373	0.99271	0.99503	0.99382
Network20	64.7377	75.1657	78.6352	72.8462	0.99399	0.99311	0.99332	0.99347
Network21	68.8056	75.3141	60.2966	68.1388	0.99382	0.99237	0.99457	0.99359

KEY: *P – Precipitation; E – Effective Drought Index; W – Available Water Resource Index (AWRI); Tr – Training; Vl – Validation; Ts – Testing; I- Inputs; T – Targets; Y-yes (included in the input/targets); N – No (Not included in the inputs/targets); Rn-Rank (The Rank of the Network by performance MSE and R); for example, Network7 has the lowest error in the Category 1 while Network14 and Network 19 have the lowest error in Category 2 and 3 respectively)*

Note: though the ranking of the networks was based on the average of the performance MSE and R) of the three data sets (Tr, Vl and Ts); the value of V1 is preferred (and was used in the actual neural networks) because it is the measure of the network's ability to carry out the future forecasting (classify dataset it has not encountered before).

Network 9 had the lowest value (**0.01887**) of MSE in the category with EDI Networks 9, 11, 12 and 14) as output. For the R value, both Networks 9 and 11 had equal values (**0.99029**). For AWRI category, the one-input **Network 17** has the best performance.

Similar tables (like Table 7-2) were plotted for Embu and Makindu leading to the following findings:

Embu: In the category of Networks for computing EDI (Networks 9, 11, 12 and 14), **Network 9** had the lowest MSE (**0.0179**) as well as the strongest R (**0.99068**). Similarly, in the category of networks that compute AWRI, **Network 17** had the lowest MSE (**64.9521**) and highest R (**0.99412**).

Makindu: Network 9 performed better among the networks with EDI as output but unlike the case of Embu and Dagoretti, **Network 21** (3 inputs) had the least MSE and **Network 19** (had EDI as the second input) had the highest value of R. Since the improvements: 51.4371 to 47.7839 (7%) for MSE and 0.99307 to 0.99361 (0.05%) were too low considering that values of extra input(s) are needed, Network 17 was selected to represent this category.

7.3 Exploratory Phase II

Using the results above, neural networks were created to forecast future values of EDI Network (9) and AWRI (Network 17) for short-term, medium-term and long-term periods as described below.

7.3.1 D-Days-Lead-Time Forecast

The lead-time (in days) considered included: 1, 2, 3, 4, 5, 6, 7, 12 and 14. Given a specific day n, to forecast EDI or AWRI value for *d*-days from n, the following expression was used:

> Forecast[E_{n+d}]=f (E_n, E_{n-1}, E_{n-2}, E_{n-3}, E_{n-4}, E_{n-5}) where E_i is the EDI value for day i; the latter ranges from 1 to 6. That is, in order to forecast future values, 6 past values were input into the neural network. In case of AWRI, E is replaced with W.
>
> For example to forecast the value of EDI 5-days Lead-Time from 21 January to 26 January, the following expression applied:
>
> Forecast[E_{21+5}]=f (E_{21}, E_{20}, E_{19}, E_{18}, E_{17}, E_{16})

For the purpose of training and testing the neural networks, the daily EDI/AWRI values for years 1980 to 2009 were used. For each of the 3 weather stations, input files for each of the neural networks (representing forecast durations above) were created. In all the networks except 12b and 14b, six number of values (EDI or AWRI) were included as inputs to the neural network models. In an attempt to find out if increasing the number of inputs would significantly improve the network performance, the number of inputs was increased to 12 and 14 in ***12b*** and ***14b*** respectively.

D-Days-Lead-Time Forecast for EDI - Results

Table 7-3: D-Days-Lead-Time Forecast – Network 9

	MSE			**RMSE**			**%RMSE**			**R**		
LT (D)	**D**	**E**	**M**	**D**	**E**	**M**	**D**	**E**	**M**	**D**	**E**	**M**
1	0.0189	0.0179	0.0197	0.137	0.134	0.140	4.15	4.49	1.84	0.9903	0.9907	0.9896
2	0.0402	0.0448	0.0318	0.201	0.212	0.178	6.06	7.09	2.52	0.9792	0.9763	0.9775
3	0.0570	0.0652	0.0569	0.239	0.255	0.239	7.21	8.55	3.76	0.9693	0.9650	0.9686
4	0.0695	0.0797	0.0818	0.264	0.282	0.286	7.96	9.46	4.86	0.9619	0.9580	0.9579
5	0.0569	0.0671	0.0552	0.239	0.259	0.235	7.20	8.68	3.68	0.9709	0.9645	0.9711
6	0.1049	0.1142	0.0992	0.324	0.338	0.315	9.78	11.32	5.60	0.9444	0.9387	0.9473
7	0.0981	0.1271	0.1184	0.313	0.356	0.344	9.46	11.94	6.38	0.9365	0.9307	0.9373
12a	0.1831	0.1862	0.1684	0.428	0.431	0.410	12.92	14.46	8.34	0.8997	0.8980	0.9077
12b	0.1838	0.1852	0.1741	0.429	0.430	0.417	12.94	14.42	8.55	0.9016	0.8976	0.9055
14a	0.2033	0.2060	0.1927	0.451	0.454	0.439	13.61	15.21	9.25	0.8897	0.8868	0.8915
14b	0.2015	0.2082	0.1217	0.449	0.456	0.349	13.55	15.29	6.52	0.8888	0.8857	0.8966

Key: *LT(D): Lead-Time in Days; D: Dagoretti Station; E: Embu station; M: Makindu station; MSE: Mean Square Error; RMSE: Root Mean Square Error – computed by calculating the square root of the MSE;%RMSE: Percentage Root Mean Square Error – calculated by computing the percentage of the actual mean values (EDI or AWRI) the RMSE represents. Example, the average AWRI for Makindu for the 30 years is 90.6. Given that the RMSE for Makindu for 7th Day Forecast for Network 17 (**Table 7-4**) is 17.8, then: %RMSE=17.6/90.6 X 100=19.6%*

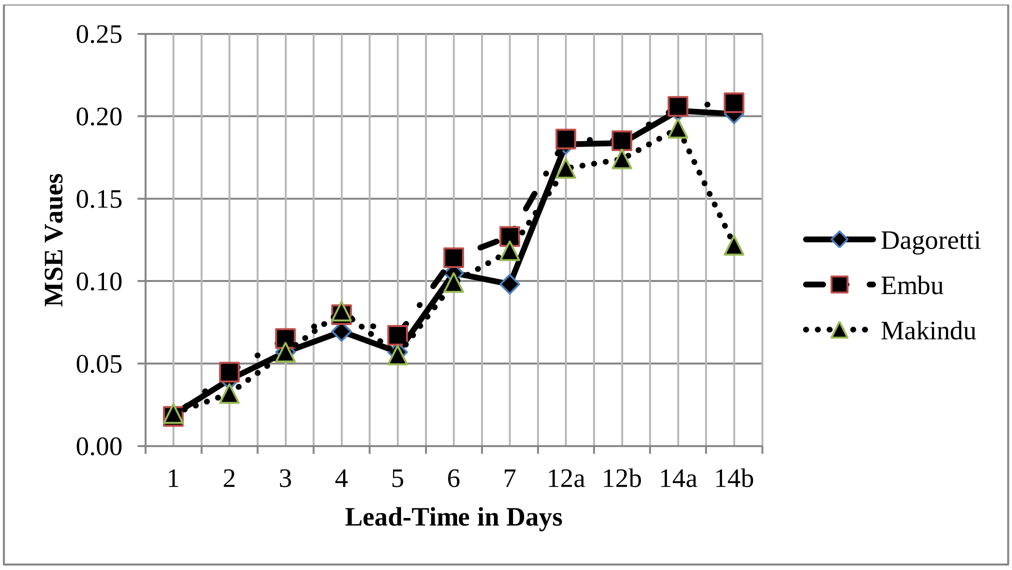


Figure 7-5: MSE Graph for D-Days-Lead-Time Forecast – Network 9

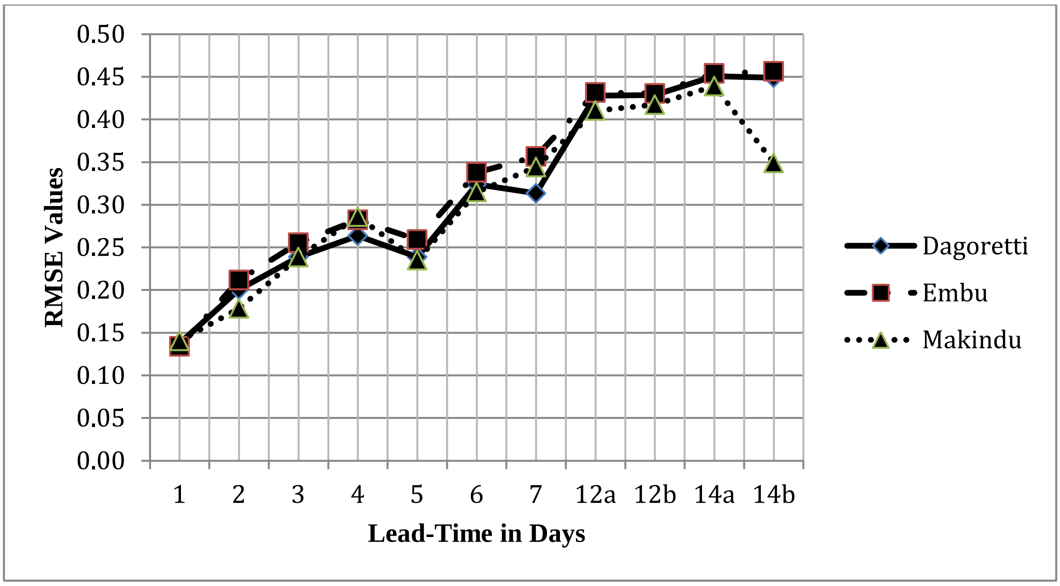


Figure 7-6: RMSE Graph for D-Days-Lead-Time Forecast – Network 9

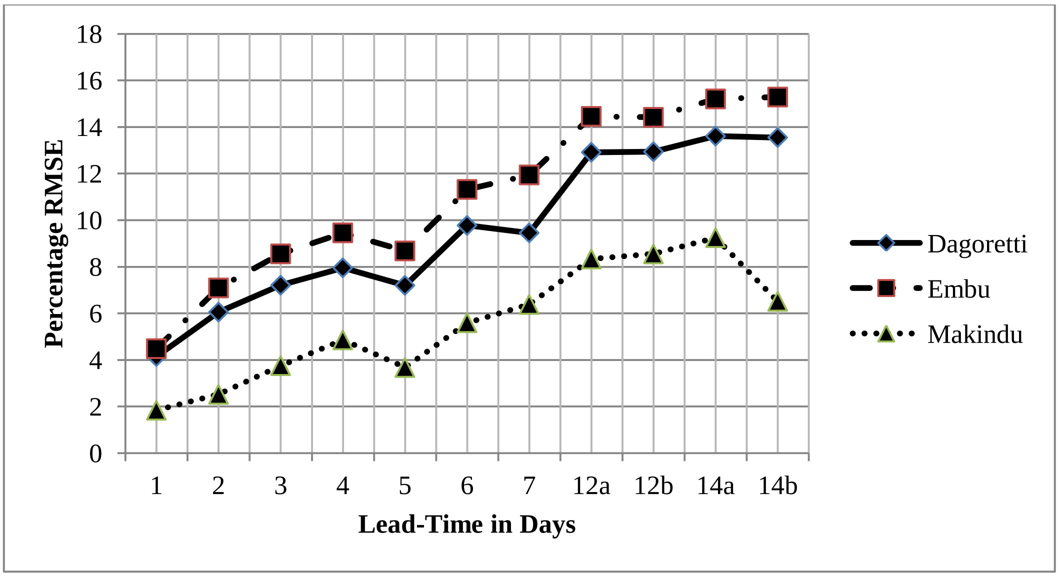


Figure 7-7: %RMSE Graph for D-Days-Lead-Time Forecast – Network 9

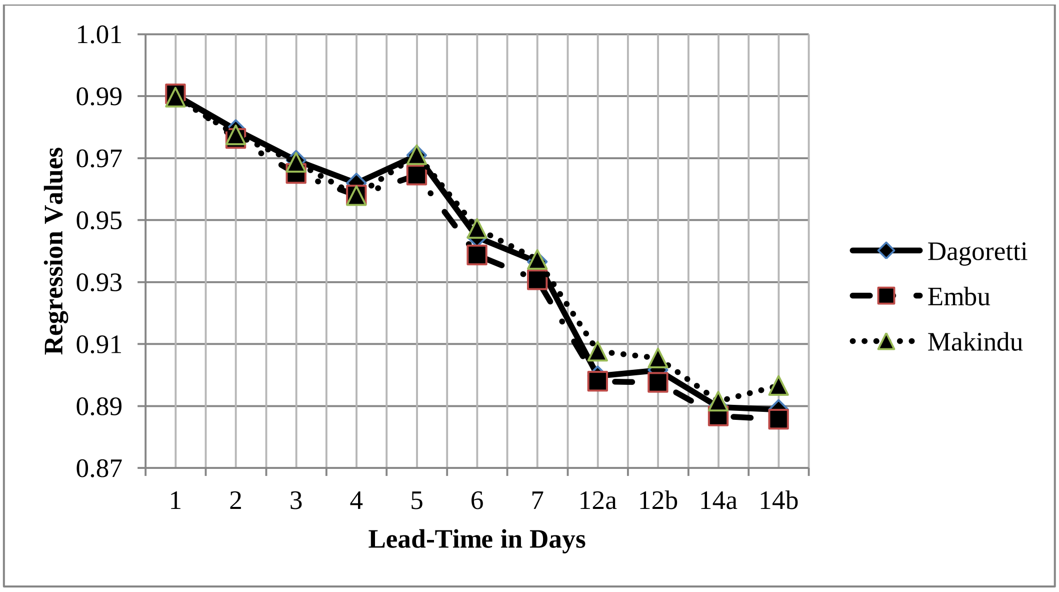


Figure 7-8: Regression Graph for D-Days-Lead-Time Forecast – Network 9

D-Days-Lead-Time Forecast for AWRI - Results

Table 7-4: D-Days-Lead-Time Forecast – Network 17

	MSE			RMSE			%RMSE			R		
LT (D)	**D**	**E**	**M**	**D**	**E**	**M**	**D**	**E**	**M**	**D**	**E**	**M**
1	67	65	51	8.2	8.1	7.2	5.20	4.14	7.92	0.9938	0.9941	0.9925
2	153	183	95	12.4	13.5	9.7	7.86	6.95	10.76	0.9860	0.9850	0.9870
3	238	276	132	15.4	16.6	11.5	9.80	8.54	12.70	0.9783	0.9779	0.9823
4	311	370	179	17.6	19.2	13.4	11.20	9.88	14.78	0.9708	0.9701	0.9746
5	231	303	141	15.2	17.4	11.9	9.66	8.94	13.11	0.9786	0.9764	0.9813
6	484	608	275	22.0	24.6	16.6	13.96	12.67	18.31	0.9552	0.9510	0.9656
7	522	667	315	22.9	25.8	17.8	14.51	13.27	19.60	0.9503	0.9428	0.9557
12a	948	1,160	544	30.8	34.1	23.3	19.55	17.50	25.75	0.9080	0.8990	0.9248
12b	959	1,166	538	31.0	34.1	23.2	19.66	17.54	25.60	0.9059	0.9019	0.9269
14a	1,136	1,398	615	33.7	37.4	24.8	21.40	19.21	27.38	0.8912	0.8749	0.9153
14b	1,075	1,393	580	32.8	37.3	24.1	20.81	19.18	26.59	0.8954	0.8841	0.9182

A plot of the AWRI values showed similar (to EDI) trend networks' performance decreased with increase in lead-time; for instance, forecasting 3 days ahead gave a better performance than forecasting 14 days head. Further, increasing the number of inputs (previous day's values) did not have a significant improvement in network performance. For example, increasing the number inputs from 6 to 14 resulted in decrease of the errors from 13.61 to 13.55%, 15.29 to 15.21% and 9.25-6.52% for Dagoretti, Embu and Makindu respectively.

7.3.2 D-Days-Lead-Time Forecast with Precipitation

In the era of climate change, extreme climate variations may trigger precipitation either during periods that it does not normally rain or lead to precipitation amounts that are below or above the expected normal for the area/region. Conventionally, ANNs-based forecasting solutions learn from past events/patterns and use this knowledge to forecast future trends. This means that faced with extreme climate variations, ANNs-based drought forecast solution would result in poor forecast skill. In order to take care of such events, the D-Days-Lead-Time Forecasting neural networks described above were modified to include forecasted precipitation values for the lead-time considered. Example, to forecast the drought (EDI and AWRI) values for the 5-days-Lead-Time counting from 21 January to 26 January, the anticipated daily precipitation (as forecast by professional weather forecasting institutions such as the KMD) for the 5 days were included as inputs to the networks:

$$\text{Forecast}[E_{21+5}]=f\ (E_{21}, E_{20}, E_{19}, E_{18}, E_{17}, E_{16}),(P_{22}, P_{23}, P_{24}, P_{25}, P_{26})$$

Where P_{is} are the forecast (approximated) precipitation values

D-Days-Lead-Time with Precipitation Forecast for EDI - Results

Table 7-5: D-Days-Lead-Time Forecast with Precipitation– Network 9

	MSE			RMSE			%RMSE			R		
	D	**E**	**M**	**D**	**E**	**M**	**D**	**E**	**M**	**D**	**E**	**M**
1	0.0047	0.0050	0.0063	0.069	0.071	0.079	2.07	2.38	0.91	0.9975	0.9973	0.9966
2	0.0108	0.0089	0.0129	0.104	0.095	0.113	3.13	3.17	1.41	0.9943	0.9926	0.9930
3	0.0168	0.0165	0.0167	0.129	0.128	0.129	3.91	4.30	1.66	0.9916	0.9914	0.9911
4	0.0248	0.0220	0.0246	0.157	0.148	0.157	4.75	4.97	2.13	0.9872	0.9883	0.9873
5	0.0274	0.0267	0.0247	0.165	0.163	0.157	4.99	5.47	2.13	0.9856	0.9858	0.9867
6	0.0300	0.0301	0.0323	0.173	0.174	0.180	5.23	5.82	2.55	0.9843	0.9837	0.9830
7	0.0378	0.0368	0.0563	0.194	0.192	0.237	5.87	6.43	3.73	0.9800	0.9801	0.9704

With accuracies of ***94.13*** to ***97.03%, 93.57*** to ***97.62%*** and ***96.25*** to ***99.09%*** for Dagoretti, Embu and Makindu respectively, the networks in the EDI category (Network 9) displayed excellent performance. Further, the networks had a correlation coefficient values between **0.98** and **0.99**. Below are sample plots showing the improvement in performance.

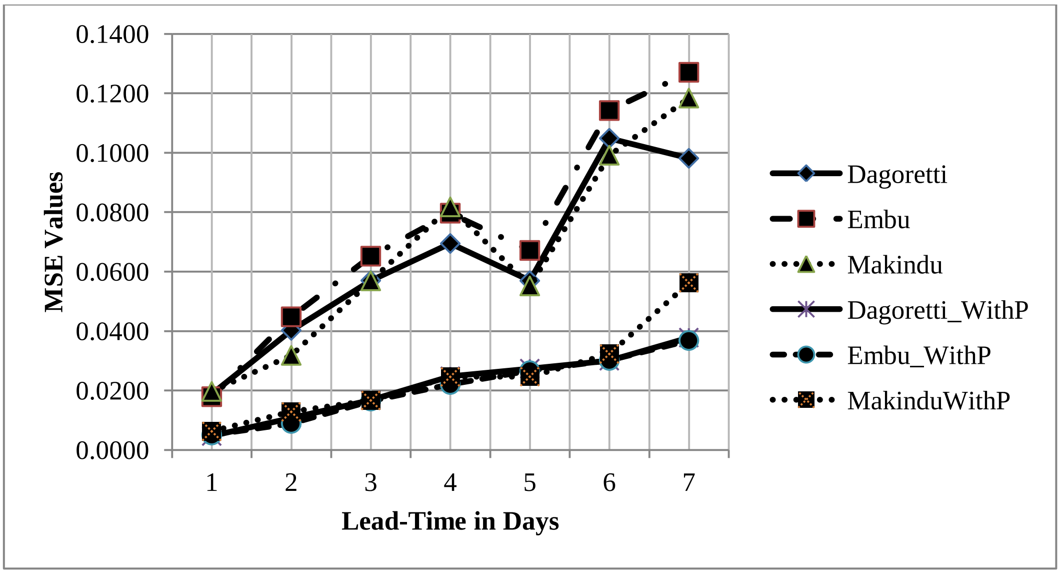


Figure 7-9: MSE Graph for D-Days-Lead-Time With Precipitation Forecast – Network 9

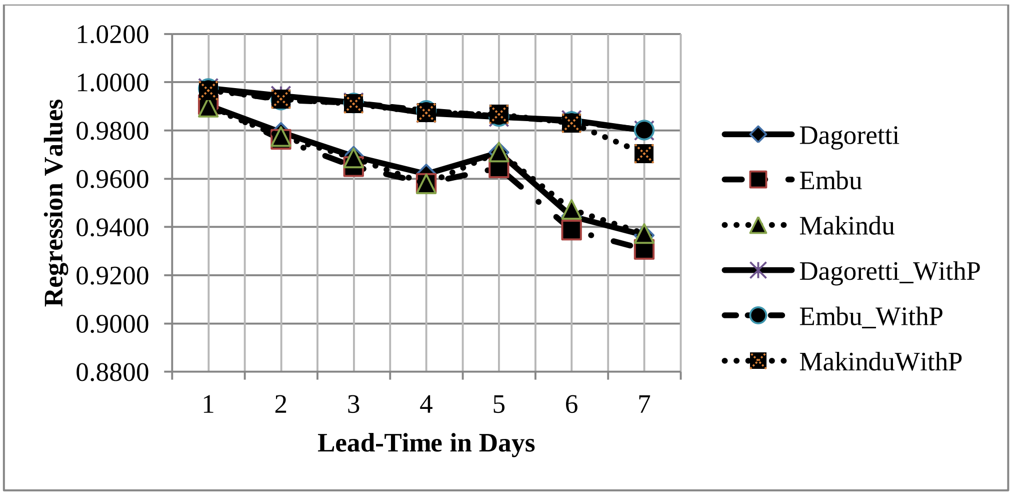


Figure 7-10: Regression Graph for D-Days-Lead-Time with Precipitation Forecast– Network 9

D-Days-Lead-Time with Precipitation Forecast for AWRI - Results

Table 7-6: D-Days-Lead-Time Forecast with Precipitation– Network 17

	MSE			RMSE			%RMSE			R		
LT (D)	**D**	**E**	**M**	**D**	**E**	**M**	**D**	**E**	**M**	**D**	**E**	**M**
1	0.4577	0.6269	0.2427	0.6765	0.7918	0.4926	0.43	0.41	0.54	0.9999	0.9999	0.9999
2	1.4443	1.5250	0.9117	1.2018	1.2349	0.9548	0.76	0.63	1.05	0.9999	0.9998	0.9999
3	2.9923	2.9578	1.2487	1.7298	1.7198	1.1174	1.10	0.88	1.23	0.9997	0.9998	0.9998
4	2.0290	3.4810	1.6987	1.4244	1.8657	1.3033	0.90	0.96	1.44	0.9998	0.9995	0.9998
5	5.9137	5.9413	3.9410	2.4318	2.4375	1.9852	1.54	1.25	2.19	0.9995	0.9995	0.9995
6	4.8063	5.2790	4.9067	2.1923	2.2976	2.2151	1.39	1.18	2.44	0.9996	0.9996	0.9993
7	8.8423	7.2963	3.8630	2.9736	2.7012	1.9655	1.89	1.39	2.17	0.9992	0.9994	0.9992

Similarly, with even higher accuracies of ***98.11*** to ***99.59%, 98.61*** to ***99.49%*** and ***98.56*** to ***99.46%*** for Dagoretti, Embu and Makindu respectively, the networks in the AWRI category (Network 17) displayed improved performance. Further, the networks had correlation coefficient values of over 0.99.

Precipitation Forecast Errors: It must be noted that the impressive performance of the D-Day-Lead-Time Forecast were achieved because the actual historical precipitation values were used as inputs. As discussed the Implementation Chapter, the implemented (post-training) networks use values forecasted by meteorological institutions. These values have accuracies as low as 70% and therefore this slightly affected the neural networks performance.

7.3.3 Next-Month-Forecast

As described in the previous Chapter, monthly EDI/AWRI values are computed using monthly precipitation totals. The output for each of the 3 weather stations takes the format [Month/Year|Precipitation|AWRI|EDI] (see Table 6-5). Using these individual output files, input/target combinations for the next month forecast neural networks were created as follows:

Network 9: $E_{n+1} = f\ (E_n, E_{n-1}, E_{n-2}, E_{n-3}, E_{n-4}, E_{n-5})$

Network 17: $W_{n+1} = f\ (W_n, W_{n-1}, W_{n-2}, W_{n-3}, W_{n-4}, W_{n-5})$

Example:

Network 9: Forecast[$E_{Jan2012}$] = f ($E_{Dec2011}$, $E_{Nov2011}$, $I_{Oct2011}$, $E_{Sep2011}$, $E_{Aug2011}$, $E_{Jul2011}$)

This is similar to the next day forecast except that the E_i and W_i represent monthly EDI and AWRI values respectively. Further, Networks 9 and 17 were selected given their superior performance in the Next Day forecast. As shown in the next 2 tables, except for Makindu, both networks resulted in poorer performance (large values of MSE and weak Regression values) than the Next-Day Forecast. However, given that the forecast duration is longer (a month as opposed to a day), the over 70% accuracy in still within acceptable ranges.

Next-Month-Forecast for EDI – Results

Table 7-7: Network Performance for the Next-Month-Forecast – Network 9

	MSE			**RMSE**			**%RMSE**			**R**		
No of Inputs	**D**	**E**	**M**	**D**	**E**	**M**	**D**	**E**	**M**	**D**	**E**	**M**
6	0.672	0.396	0.244	0.820	0.629	0.494	24.17	24.47	13.50	0.8037	0.7712	0.8289
12	0.601	0.332	0.229	0.776	0.576	0.478	21.65	22.40	12.85	0.7465	0.7879	0.7979
14	0.608	0.337	0.325	0.780	0.580	0.570	21.89	22.56	16.87	0.7540	0.7883	0.8186
18	0.618	0.354	0.396	0.786	0.595	0.629	22.23	23.14	19.74	0.7321	0.7970	0.7990

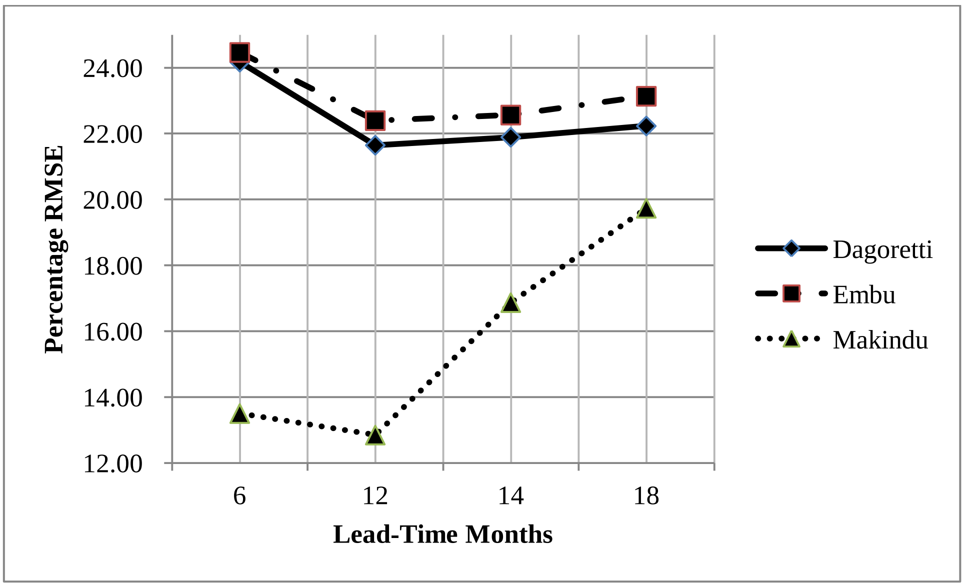


Figure 7-11: %RMSE Graph for Next-Month-Forecast – Network 9

Next-Month-Forecast for AWRI – Results

Table 7-8: Network Performance for the Next-Month-Forecast – Network 17

	MSE			**RMSE**			**%RMSE**			**R**		
No of Inputs	**D**	**E**	**M**	**D**	**E**	**M**	**D**	**E**	**M**	**D**	**E**	**M**
6	8,420	8,876	4,004	91.8	94.21	63.28	27.93	23.21	33.43	0.7996	0.7463	0.7671
12	6,487	7,136	3,219	80.5	84.48	56.74	24.51	20.81	29.97	0.8281	0.8568	0.8815
14	8,217	7,294	5,493	90.6	85.40	74.11	27.59	21.04	39.15	0.8026	0.8274	0.8520
18	8,038	8,743	3,751	89.7	93.51	61.25	27.28	23.03	32.35	0.7795	0.8083	0.8675

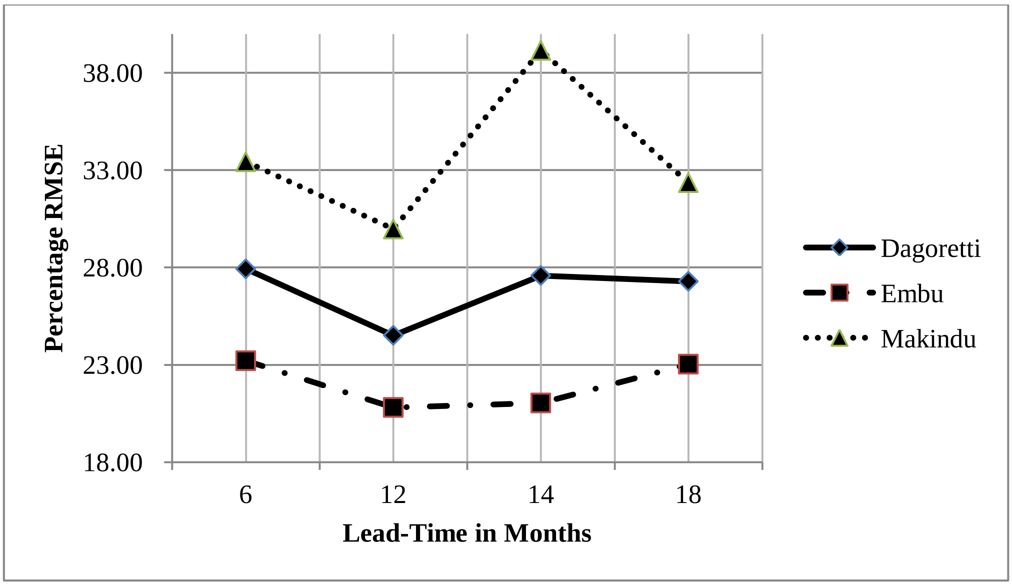


Figure 7-12: %RMSE Graph for Next-Month-Forecast – Network 17

The best performing networks were those with 12 previous months as input. Forecasts were repeated using 24 and 36 months respectively and despite producing MSE values in the same range as in ***Tables 7-7*** and ***7-8***, the R values were 0 in all tests. This indicated that there was no correlation between the forecast and actual values and therefore these forecasts were discarded.

7.3.4 M-Months-Lead-Time Forecast

Though results in ***section 7.3.3*** indicate that twelve number of inputs had the best performances, the improvements (for example 72 – 75%, 77 – 79% and 60 to 67% for Dagoretti, Embu and Makindu respectively) was minimal given that the inputs were double (6 to 12). 6 inputs (previous months) were therefore selected as the standard input in training neural networks to forecast monthly EDI/AWRI values. The lead-time units considered were 1, 3, 6, 9 and 12 months.

Given a month n, to forecast EDI/AWRI the EDI/AWRI value *m* months from n, the following expression was used:

$\text{Forecast}[E_{n+m}]=f(E_n, E_{n-1}, E_{n-2}, E_{n-3}, E_{n-4}, E_{n-5})$ where E_i is the EDI value for month i; the latter ranges from 1 to 6. That is, in order to forecast future values, 6 past values are input into the neural network. In case of AWRI, E is replaced with W. For example to forecast the value of EDI 6-months Lead-Time from January 2012 (that is forecast for July 2012), the following expression applies:

$$\text{Forecast}[E_{Jul\text{-}2012}]=f\,(E_{Jan\text{-}2012}, E_{Dec\text{-}2011}, E_{Nov\text{-}2011}, E_{Oct\text{-}2011}, E_{Sep\text{-}2011}, E_{Aug\text{-}2011})$$

M-Months-Lead-Time Forecast for EDI - Results

Table 7-9: M-Months-Lead-Time Forecast – Network 9

LT (M)	**MSE**			**RMSE**			**%RMSE**			**R**		
	D	**E**	**M**	**D**	**E**	**M**	**D**	**E**	**M**	**D**	**E**	**M**
1	0.552	0.556	0.514	0.743	0.746	0.717	26.75	29.01	24.37	0.6868	0.6713	0.7432
3	0.750	0.758	0.625	0.866	0.871	0.791	31.17	33.86	28.59	0.5483	0.4733	0.6317
9	0.862	0.997	0.868	0.928	0.999	0.932	33.42	38.84	37.60	0.3359	0.1837	0.2477
12	0.809	1.087	1.009	0.900	1.043	1.004	27.15	34.93	36.27	0.3970	0.2593	0.4995

Values 1, 3. …,12 represent the lead-time of the forecast in months. For example, entry 5 implies that the forecast is for the fifth month given the previous six months.

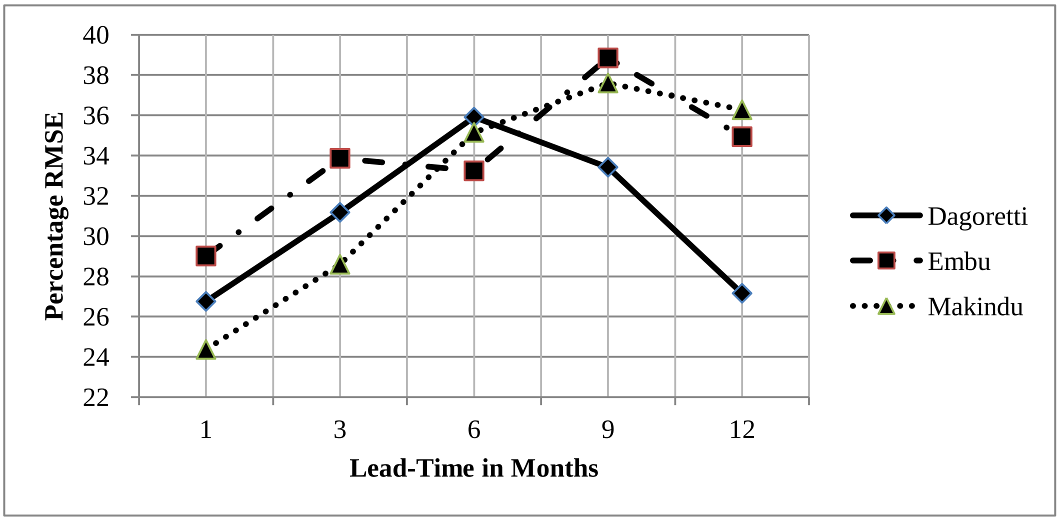


Figure 7-13: %RMSE Graph for M-Month-Lead-Time Forecast – Network 9

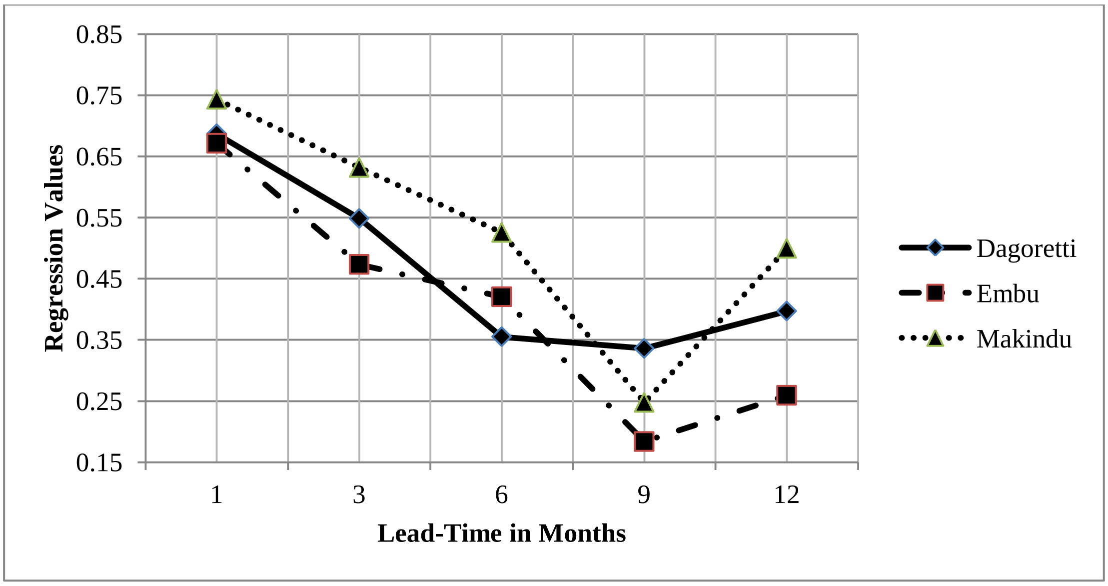


Figure 7-14: Regression Graph for M-Month-Lead-Time Forecast – Network 9

M-Months-Lead-Time Forecast for AWRI - Results

Table 7-10: M-Month-Lead-Time Forecast – Network 17

	MSE			**RMSE**			**%RMSE**			**R**		
LT (M)	**D**	**E**	**M**	**D**	**E**	**M**	**D**	**E**	**M**	**D**	**E**	**M**
1	12,858	15,076	10,693	113	123	103	35	30	55	0.5849	0.5452	0.6651
3	21,444	19,728	11,785	146	140	109	45	35	57	0.3489	0.4688	0.5066
6	21,335	19,405	13,654	146	139	117	44	34	62	0.3991	0.5290	0.3350
9	25,778	20,336	15,095	161	143	123	49	35	65	0.3825	0.4703	0.3868
12	16,408	20,643	15,034	128	144	123	81	74	135	0.5158	0.5006	0.4094

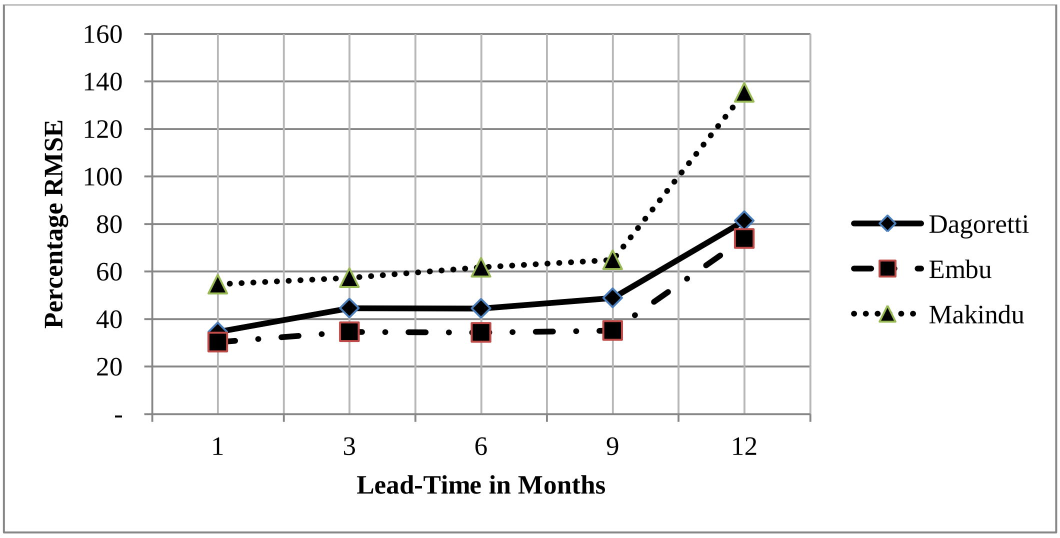


Figure 7-15: %RMSE Graph for M-Month-Lead-Time Forecast – Network 17

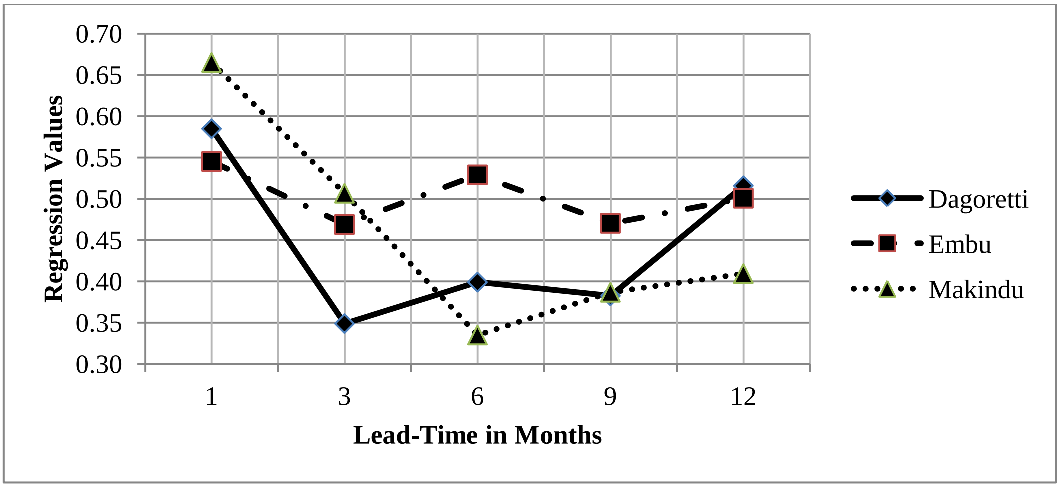


Figure 7-16: Regression Graph for M-Month-Lead-Time Forecast – Network 17

As shown in the graphs/tables above, the performance of the neural networks decreases as the length of the forecast duration increases. In the majority of the cases, there seem to be an ***optimum*** point the lead-time of the forecast is 5 months. However, the error rates for majority of the networks are above 30% resulting in forecasts that with below 70% accuracy.

7.3.5 Next-Year-Forecast

As described in Chapter 6, the formula for computing EDI/AWRI provides a strong correlation among values of same calendar month/day of different years. For example, the EDI value for January 2000 has some correlation with EDI value for January, 1999, January 2001, January 2002 and so on. Using this fact, an attempt to create/train/evaluate neural networks to check for these relations was made using the monthly data. As mentioned under 'D-Days-Lead-Time Forecast with Precipitation' section, the EDI/AWRI values are dependent on the precipitation values and as such, a significant increase/decrease of the 'normal' annual precipitation values during the forecast will lead to inaccurate results. To address this, the annual precipitation totals for both the previous year(s) considered and an approximated value (the actual values were used in this phase, predicted values were used in actual forecasting described later) for the year being forecast were included.

Example 1: Y=1

Network 9: $E_{\text{MonthM, Year y+1}} = f\,(E_{\text{MonthM, Year y}}, P_{\text{Year y}}, P_{\text{Year y+1}})$

Network 17: $W_{\text{MonthM, Year y+1}} = f\,(W_{\text{MonthM, Year y}}, P_{\text{Year y}}, P_{\text{Year y+1}})$

Where P is the total annual precipitation for a given year

Illustration: given EDI/AWRI value for January 2009 ($E_{MonthM,\ Year\ y}$ or $W_{MonthM,\ Year\ y}$), total annual precipitation for 2009 ($P_{Year\ y}$) and approximated total annual precipitation for 2010 ($P_{Year\ y+1}$), forecast the EDI/AWRI value for January 2010.

Example 2: Y=2

Network 9: $E_{MonthM,\ Year\ y+1} = f(E_{MonthM,\ Year\ y-1}, E_{MonthM,\ Year\ y}, P_{Year\ y-1}, P_{Year\ y}, P_{Year\ y+1})$

Network 17: $W_{MonthM,\ Year\ y+1} = f(W_{MonthM,\ Year\ y-1}, W_{MonthM,\ Year\ y}, P_{Year\ n-1}, P_{Year\ y}, P_{Year\ y+1})$

Example 3: Y=6

Network 9: $E_{MonthM,\ Year\ y+1} = f(E_{MonthM,\ Year\ y-5}, E_{MonthM,\ Year\ y-4}, E_{MonthM,\ Year\ y-3}, E_{MonthM,\ Year\ y-2}, E_{MonthM,\ Year\ y-1}, E_{MonthM,\ Year\ y}, P_{Year\ y-5}, P_{Year\ y-4}, P_{Year\ y-3}, P_{Year\ y-2}, P_{Year\ y-1}, P_{Year\ y}, P_{Year}\ Y_{y+1})$

Network 17: $W_{MonthM,\ Year\ n+1} = f(W_{MonthM,\ Year\ n-5}, W_{MonthM,\ Year\ n-4}, W_{MonthM,\ Year\ n-3}, W_{MonthM,\ Year\ n-2}, W_{MonthM,\ Year\ n-1}, W_{MonthM,\ Year\ n}, P_{Year\ n-5}, P_{Year\ n-4}, P_{Year\ n-3}, P_{Year\ n-2}, P_{Year\ n-1}, P_{Year\ n}, P_{Year\ n+1})$

Illustration: to forecast EDI/AWRI values for August 1986, the neural network requires the EDI/AWRI values for August 80, 81, 82, 83, 84 and 85. It also requires the annual precipitation totals for these years as well as an approximate annual precipitation value for year 1986.

Next-Year-Forecast for EDI - Results

Table 7-11: Next-Year-Forecast – Network 9

	MSE			RMSE			%RMSE			R		
	D	E	M	D	E	M	D	E	M	D	E	M
2	0.328	0.395	0.302	0.572	0.629	0.550	20.60	24.45	15.94	0.7826	0.8114	0.8249
3	0.350	0.297	0.234	0.591	0.545	0.483	21.29	21.18	13.06	0.7527	0.8709	0.8724
4	0.224	0.218	0.205	0.473	0.467	0.453	17.03	18.17	11.81	0.8521	0.8761	0.8516
5	0.375	0.233	0.245	0.612	0.483	0.495	22.04	18.77	13.53	0.7645	0.8853	0.8902
6	0.290	0.368	0.260	0.539	0.606	0.510	19.39	23.58	14.19	0.8277	0.8672	0.8779
7	0.458	0.382	0.443	0.676	0.618	0.666	24.35	24.03	21.59	0.6198	0.8411	0.8122

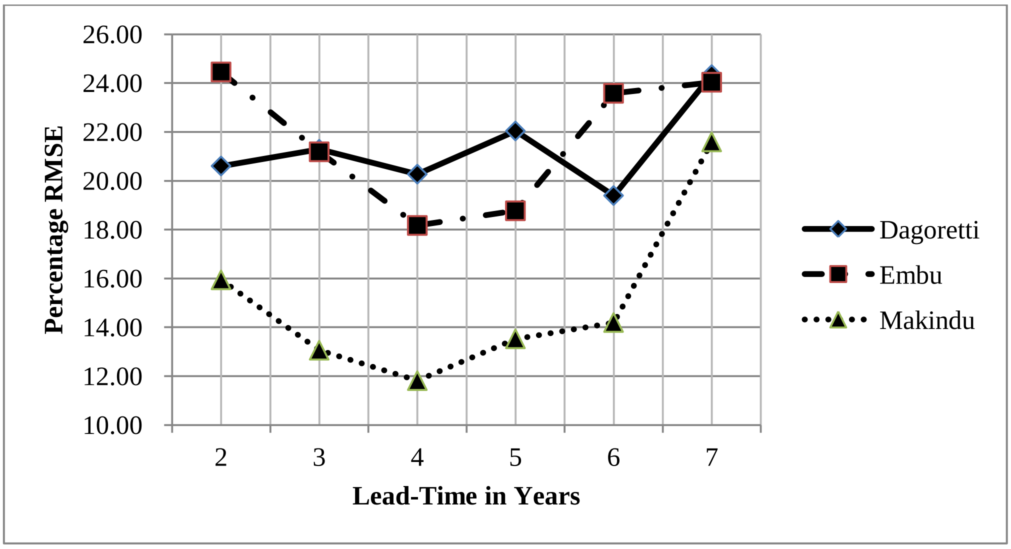


Figure 7-17: %RMSE Graph for Next-Year-Forecast – Network 9

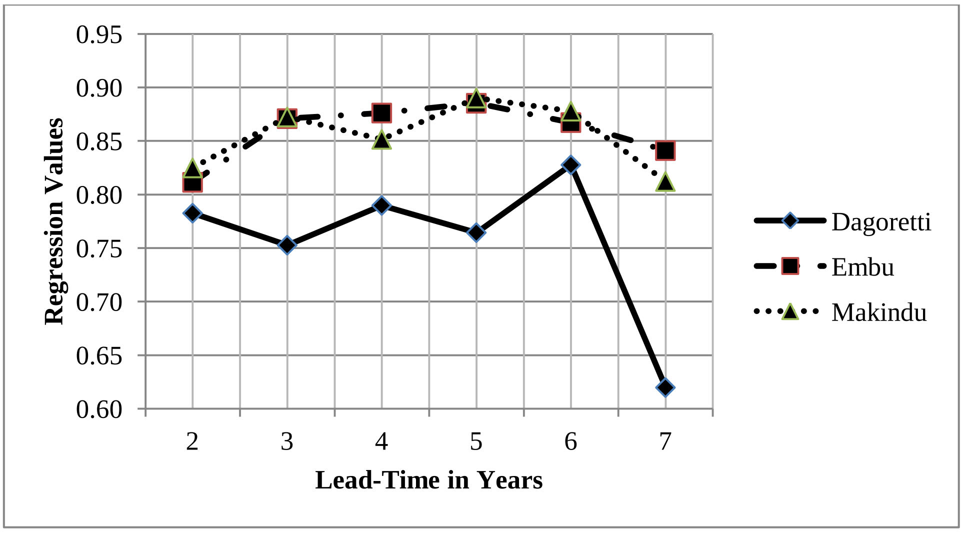


Figure 7-18: Regression Graph for Next-Year-Forecast – Network 9

Next-Year-Forecast for AWRI - Results

Table 7-12: Next-Year-Forecast – Network 17

	MSE			RMSE			%RMSE			R		
	D	**E**	**M**	**D**	**E**	**M**	**D**	**E**	**M**	**D**	**E**	**M**
2	13,231	15,852	10,656	115.0	125.9	103.2	35.01	31.01	54.53	0.6524	0.5493	0.6180
3	12,302	9,240	6,196	110.9	96.1	78.7	33.75	23.68	41.58	0.7403	0.7971	0.7155
4	7,075	8,976	3,556	84.1	94.7	59.6	25.60	23.34	31.50	0.8319	0.8166	0.8816
5	7,475	6,526	3,037	86.5	80.8	55.1	26.31	19.90	29.11	0.8347	0.8771	0.9018
6	6,651	7,030	5,407	81.6	83.8	73.5	24.82	20.65	38.84	0.8571	0.8838	0.8575
7	5,770	8,090	5,465	76.0	89.9	73.9	23.12	22.15	39.05	0.8766	0.8396	0.7704

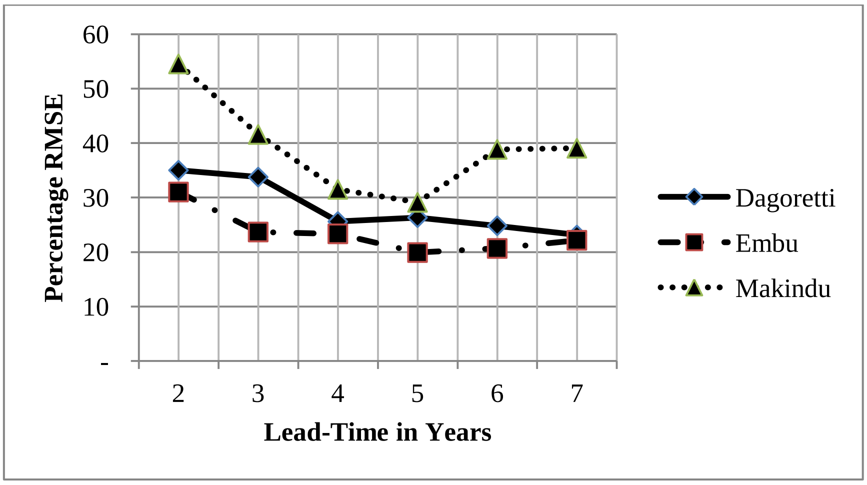


Figure 7-19: %RMSE Graph for Next-Year-Forecast – Network 17

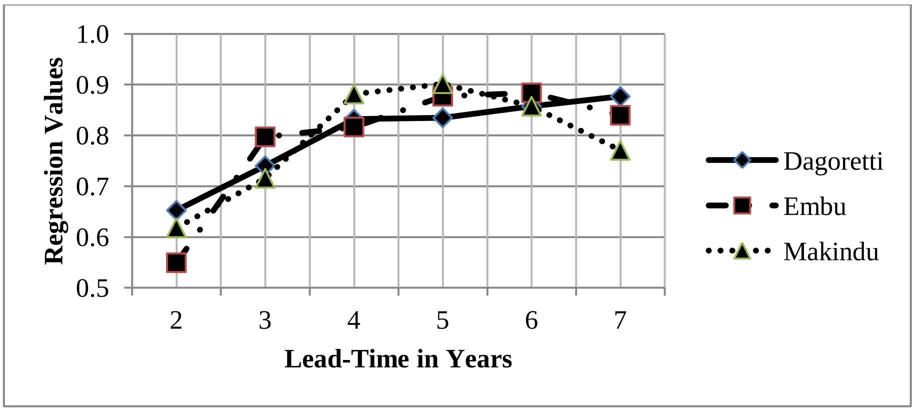


Figure 7-20: Regression Graph for Next-Year-Forecast – Network 17

The results above indicate that including past data for more than 4 years resulted in degradation of the performance. With accuracy of over 75% and regression values of over 0.8, this category of networks had improved performance in forecasting EDI (Network 9) values for forecasting period of 1 year. However, though computation of AWRI values had impressive regression values, the accuracy of most of networks (except for Makindu) was about 70%.

7.3.6 Y-Years-Lead-Time Forecasting

The impressive results of Next-Year-Forecast were used to carry out forecast for Y(1,2,3 and 4) years Lead-Time as described below.

Y-Years-Lead-Time Forecast for EDI - Results

Table 7-13: Y-Years-Lead-Time Forecast – Network 9

	MSE			**RMSE**			**%RMSE**			**R**		
	D	**E**	**M**	**D**	**E**	**M**	**D**	**E**	**M**	**D**	**E**	**M**
1	0.224	0.218	0.205	0.473	0.467	0.453	17.03	18.17	11.81	0.8521	0.8761	0.8516
2	0.305	0.305	0.233	0.552	0.552	0.482	19.87	21.47	13.02	0.8389	0.8618	0.9107
3	0.294	0.294	0.267	0.542	0.542	0.516	19.51	21.10	14.46	0.7953	0.8504	0.8682
4	0.285	0.315	0.270	0.533	0.561	0.520	19.20	21.83	14.60	0.8487	0.8167	0.8527

Y-Years-Lead-Time Forecast for AWRI - Results

Table 7-14: Y-Years-Lead-Time Forecast – Network 17

	MSE			**RMSE**			**%RMSE**			**R**		
	D	**E**	**M**	**D**	**E**	**M**	**D**	**E**	**M**	**D**	**E**	**M**
1	7,475	6,526	3,037	86.5	80.8	55.1	26.31	19.90	29.11	0.8347	0.8771	0.9018
2	7,709	5,085	3,406	87.8	71.3	58.4	26.72	17.56	30.83	0.7414	0.9063	0.9036
3	9,929	6,251	4,070	99.6	79.1	63.8	30.32	19.47	33.70	0.8221	0.8689	0.8296
4	10,037	9,332	4,661	100.2	96.6	68.3	30.49	23.79	36.06	0.8250	0.7860	0.8242

As in the case of Next-Year forecast, Network 9 had an accuracy of over 75% in all the cases. Once more, Network 17 had poorer performance especially when forecasting for Lead-Time greater than 2 years.

7.4 Confirmatory Phase

7.4.1 Overview

In this phase, data for a weather station that was not used in the previous two phases was used to confirm the findings so far. From the exploratory phase, the following networks were identified for this confirmation: D-Days-Lead-Time Forecasting, D-Days-Lead-Time Forecasting with Precipitation and Y-Years-Lead-Time Forecast. Data-set for Kakamega weather station with same dimensions as the data for Dagoretti, Embu and Makindu was used to evaluate the performance of the ANNs models. For each forecast category, the already trained networks were retrieved and used to evaluate the respective networks' input-output combinations created using the Kakamega data set. Below are the results:

7.4.2 D-Days-Lead-Time Forecasting

Table 7-15: D-Days-Lead-Time Forecast for Kakamega– Network 9

Day	MSE	RMSE	%RMSE	R
2	0.0639	0.253	6	0.9660
3	0.0911	0.302	8	0.9518
4	0.1181	0.344	9	0.9377
5	0.0857	0.293	7	0.9503
6	0.1616	0.402	10	0.9132
12	0.3186	0.564	14	0.8221

Table 7-16: D-Days-Lead-Time Forecast for Kakamega– Network 17

Day	MSE	RMSE	%RMSE	R
2	221	14.9	5.01	0.9754
3	296	17.2	5.80	0.9667
4	340	18.4	6.22	0.9592
5	286	16.9	5.70	0.9677
6	552	23.5	7.92	0.9393
12	1,261	35.5	11.97	0.8617

7.4.3 D-Days-Lead-Time Forecasting with Precipitation

Table 7-17: D-Days-Lead-Time Forecast With Precipitation for Kakamega– Network 9

Day	MSE	RMSE	%RMSE	R
1	0.0086	0.093	2	0.9959
2	0.0167	0.129	3	0.9922
3	0.0228	0.151	4	0.9855
4	0.0367	0.192	5	0.9889
5	0.0386	0.196	5	0.9803
6	0.0536	0.232	6	0.9750
7	0.0658	0.257	7	0.9701

Table 7-18: D-Days-Lead-Time Forecast With Precipitation for Kakamega– Network 17

	MSE	RMSE	%RMSE	R
2	221	14.9	5.01	0.9754
3	296	17.2	5.80	0.9667
4	340	18.4	6.22	0.9592
5	286	16.9	5.70	0.9677
6	552	23.5	7.92	0.9393
12	1,261	35.5	11.97	0.8617

7.4.4 Y-Years-Lead-Time Forecast

Table 7-19: Y-Years-Lead-Time Forecast With Precipitation for Kakamega– Network 9

	MSE	RMSE	%RMSE	R
1	0.6372	0.798	20	0.8382
2	0.6960	0.834	21	0.7800
3	0.6161	0.785	20	0.7580
4	0.9129	0.955	24	0.7249

In all the three forecast categories (shown above) evaluated, the resulting network accuracies were within the same ranges as those in the Exploratory Phase.

8. Drought Communication and Dissemination

8.0 Introduction

The third component of the Drought Early Warning System is '**Communication and Dissemination'**. It is here that the following general questions are answered (ISDR 2006): (1) Do drought warnings reach all of those at risk? (2) Are the risks and the warnings understood? (3) Is the warning information clear and useable?

It is therefore imperative that this component meets users' needs because this affects the success of the DEWS; transitively, its design determines the extent to which the system meets the specific users' needs. As discussed elsewhere in this thesis, our system specifically targets the small-scale farmers whose main ICTs tool is the mobile phone. In an effort to maximise the chances of the system's success, user interfaces with the system were implemented around the mobile phone, this included, Short Message Service (SMS) and mobile application. The use of sensors to capture weather data was a phenomenal contribution of this research; in order to allow access to this data, as well as the data on droughts, to researchers, business people (such as the insurance industry) and civil society, a comprehensive web portal was also implemented.

For users that cannot read, a text-to-speech translation facility was implemented; it generates sound files of drought/weather forecasts. Given that drought and weather are intertwined, a weather forecasts dissemination module was implemented to create synergies between the SCFs and the IKFs. Extreme weather events (such as landslides and flash floods) alert system was incorporated as part of the weather forecast module. For the purpose of collecting and storing IK on weather/droughts, a mobile phone application was implemented on Android platform.

In this chapter, the analysis, design, implementation and testing of the integrated DEWS is described in details. The working of the system can be found on the project's website at: http://www.eastafricaweather.com.

8.1 System Overview and Use Case

In line with the DEWS Framework presented in Chapter 4, the system was implemented in three layers: one layer for each of the three components.

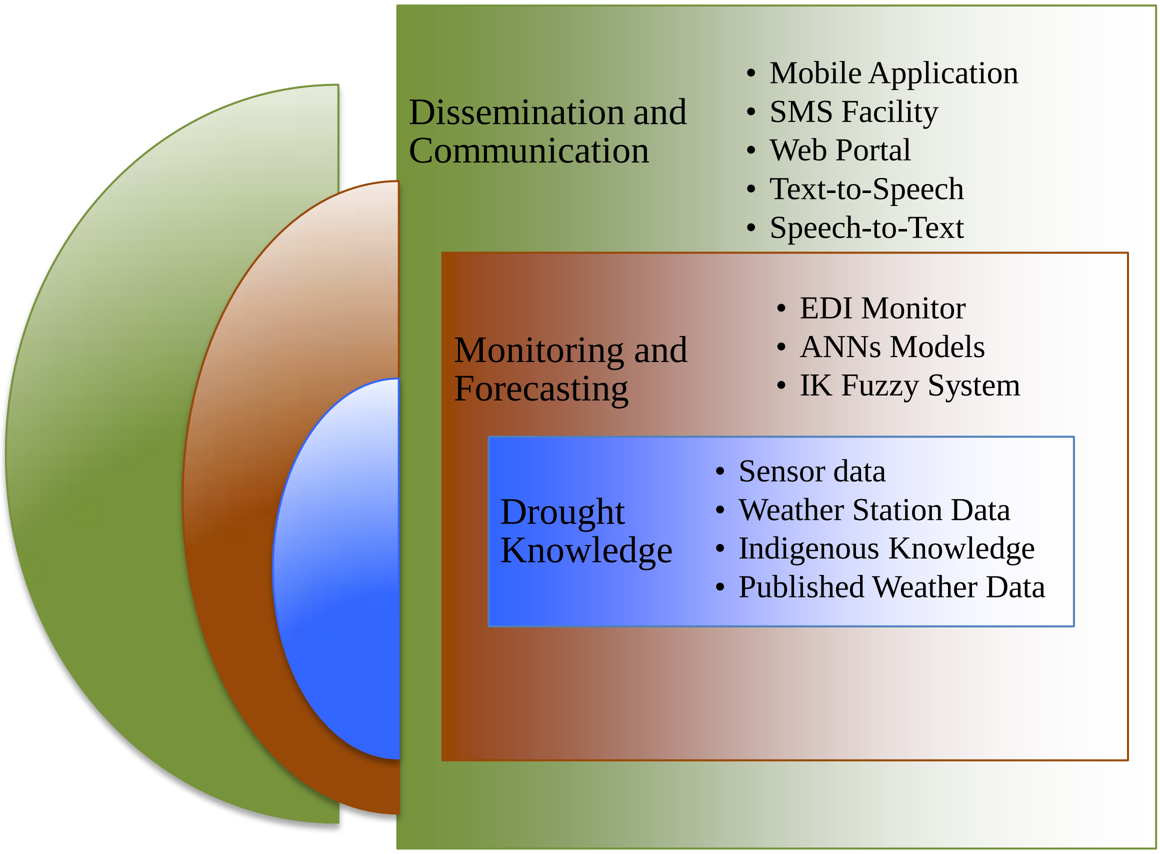


Figure 8-1: Architecture of the System Prototype

Drought Knowledge

Sensor data from sensors is sent to a MySQL database via a java-based SMS gateway. **Weather Station Data** and **Indigenous Knowledge** is captured into the system via a web interface and a mobile phone application respectively; the details are presented later in chapter. In its current form, our DEWS prototype does not carry out weather forecast; such information is retrieved from **Published Weather Data** especially from KMD's weather reports.

Monitoring and Forecasting

The data collected and stored in the Drought Knowledge layer is used by the following: (1) **EDI Monitor** that takes care of the 'Monitoring' aspect; this is implemented as a stand-alone FORTRAN program. The output in form of text files are then used to run insert queries to populate the database; (2) **ANNs models** that were implemented in MATLAB are used to forecast future values of drought in terms of EDI and AWRI; and (3) **IK Fuzzy Logic System** handles the monitoring and forecasting of drought using indigenous knowledge. This was also implemented in MATLAB; its output is uploaded to the MySQL database from where it is linked to the ANNs models' output.

Dissemination and Communication

The system is accessible to end users via five input/output channels: (1) **Mobile Application** that is used for inputting and outputting IK indicators and extreme weather events; (2) **SMS Facility** for requesting drought and weather forecasts as well for extreme weather events alerts; (3) **Web Portal** which is used to access comprehensive information on droughts, weather and extreme events. Formats available include text, graphs and audio files; (4) **Text-to-Speech** is simple plug-in implemented to generate audio formats of the drought and weather forecasts; and (5) **Speech-to-Text** which is also a plug-in of the android phone; it is used as an alternative to typing input data via the android application.

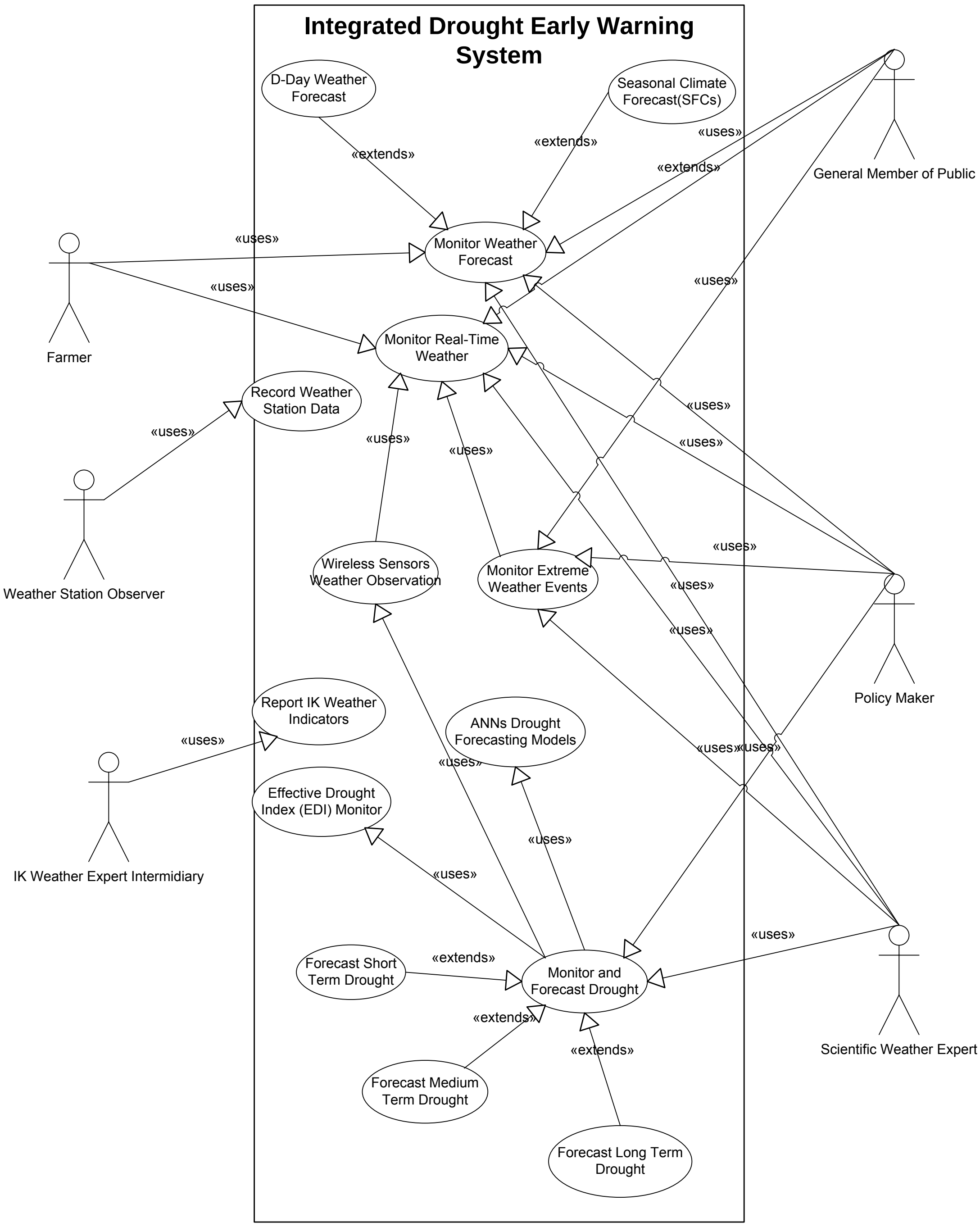


Figure 8-2: DEWS' Use Case Diagram

8.2 System Layer 1 – Drought Knowledge Capture

8.2.1 System Layer 1 – the Logic

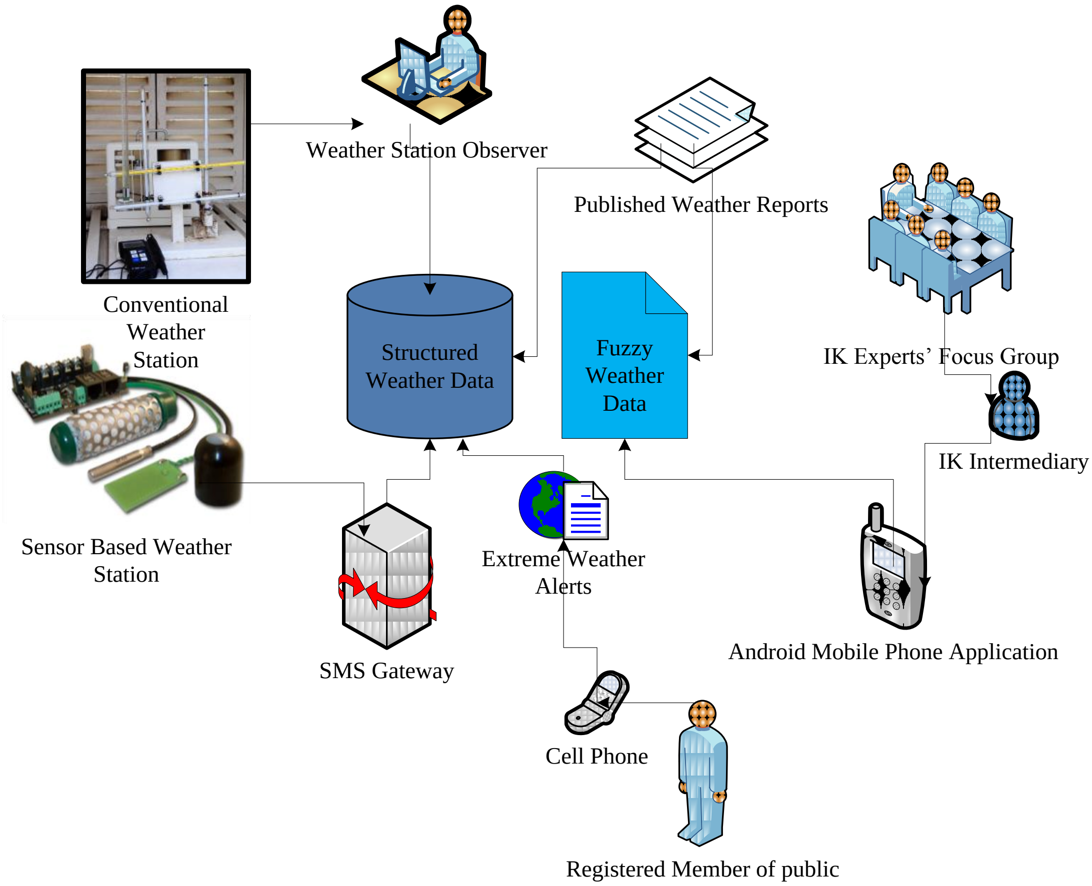


Figure 8-3: System Layer 1 – the Logic

8.2.2 Mobile Phone Application

This application is used by an intermediary acting on behalf of a focus group made of IK Experts. Information on IK Indicators expected from the community that the intermediary represents was pre-captured in the database described above. After reaching an agreement on the observed indicators for a given period (a day, a week, a month, and so on), the intermediary logs on to the mobile application and selects a list of indicators observed; the application associates these with the period specified and upload them to the database. In order to take care of slow/absence of internet, the application first saves the records to a local database before transmitting them to the remote database. The second functionality of this application is to allow the intermediary to send in observed extreme weather events.

Mobile Application Design and Implementation

This is an Android Application that captures two pieces of information; ***extreme weather events*** and ***indigenous knowledge weather indicators***. It is implemented using four main classes and 3 supporting packages; ***updates***, ***db*** and ***utils***.

Figure 8-4: Mobile Application Class Diagram

ChooseActionSubmitActivity.java class is the 'menu' of the application; it displays the login screen and the prints out the Main Menus Options after successful login. ***ExtremeSubmitActivity.java*** and ***IndigenousKnowledgeAppActivity.java*** handle the submission and retrieval of extreme weather events and indigenous knowledge indicators tasks respectively. ***FormSubmitActivity.java*** is the main class that receives the data from the user and communicates with the database (local and remote). The four classes use helper packages: ***db*** and ***updates*** which manages the local and remote databases connections and ***utils*** that synchronises the local (on the phone) and remote copies of IK indicators and extreme events.

System Testing

Implementation Platform: The Application runs on Hawaei IDEAOS handset shown below:

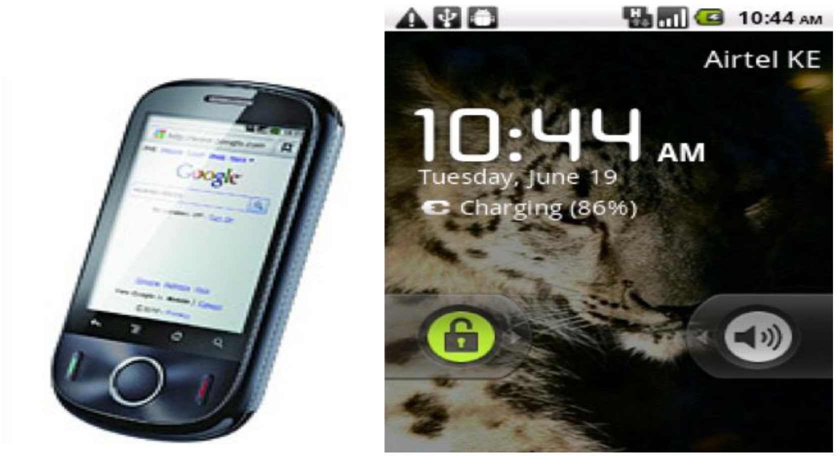


Figure 8-5: Mobile Application Implementation Phone

Application Installation: The mobile application is uploaded to the phone and installed using ASTRO utility. Once installed it appears under the application name; ‘***IK Weather Monitor’*** as shown below.

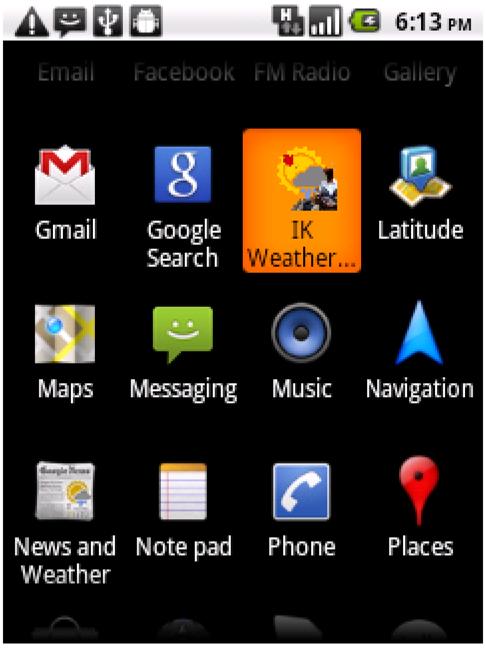


Figure 8-6: Mobile Application Icon

Application Functionalities: To ensure that only the authorised IK experts' intermediary is allowed to use the system, the application starts off with a **Login Screen** for authentication. After successful login, the **Main Menu** with three options as shown below appears.

Figure 8-7: Mobile Application Main Menu

IK Weather Observations Sub-Menu: captures the indigenous weather indicators as observed and agreed by IK Experts' Focus Groups. For consistency and error reduction, all known indicators for each community/region are pre-stored in the database. All the users need to do is to select from the list by clicking on the down arrow.

Figure 8-8: Mobile Application - IK Indicators Sub-Menu

Extreme Weather Event Sub-Menu: Opens the screen below to allow for entry of extreme weather events. The events are classified as ether Mild, Serious or Severe and the user gets to select one of these by clicking on the down arrow.

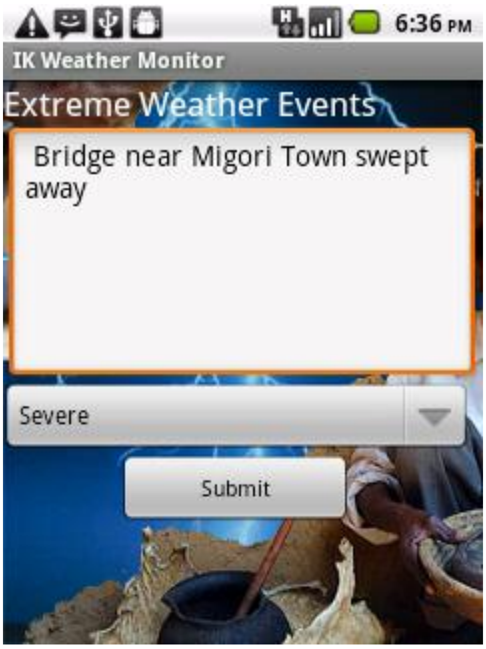


Figure 8-9: Mobile Application - Extreme Weather Events Sub-Menu

Speech to Text Facility: The system integrates the use of the '*Sound Record'* facility of the IDEOS phone; this is done by simply clicking on the 'Record' key on the phone and then recording the text (IK indicator or Extreme Event). This aspect was incorporated to illustrate how illiterate/semi-illiterate users could use the system to input observed IK indicators or/and extreme events. However, the component is currently not operational and further work is needed in order to enable local (used by the illiterate/semi-illiterate users, kimbeere for example) languages translation in to English.

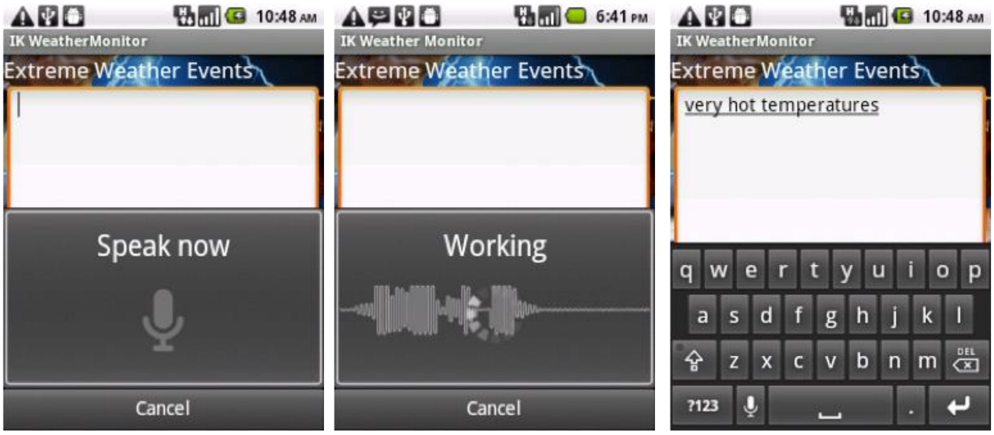


Figure 8-10: Mobile Application – Text-to-Speech Facility

Saving Records: Once the user clicks on the submit button to save the record, a copy of the record is first saved locally in a database on the phone and when/if internet connection is available, a copy is sent to the remote database.

SMS Facility: Allows registered (with our DEWS) members of public to send in any extreme weather events they may observe; such alerts are first vetted before being disseminated to stakeholders.

8.2.3 Sensor-Based Weather Station

After the rigorous sensor calibration exercise that was described in Chapter 5, the calibrated sensor boards were used to design a weather monitoring system prototype. Two types of deployments were set up:

Sensor Boards Next to Weather Stations

Here, sensor boards were placed within the Observatory Unites of selected weather stations in Kenya. The boards individually sent readings to a remote database via an

SMS Gateway. The sensors included were those for measuring temperature, relative humidity and atmospheric pressure. In a few of the locations, rainfall, wind speed, wind direction, and soil moisture sensors were installed. Aggregation of multiple sensor readings was performed using Option 2 described in Chapter 5. Apart from monitoring weather, this set up sought to further validate the calibration decisions.

Stand-Alone Sensor Boards

In order to deploy the sensors in the rural areas especially in Mbeere and Bunyore on which the IK case study was based, stand-alone sensors mounted with temperature, relative humidity and atmospheric sensors were used. The sensors boards were placed inside traditional granaries which provided environment almost similar to the one supported by the Shenstone Screens.

Figure 8-11: A Traditional Granary in one of the Mbeeres' Participants

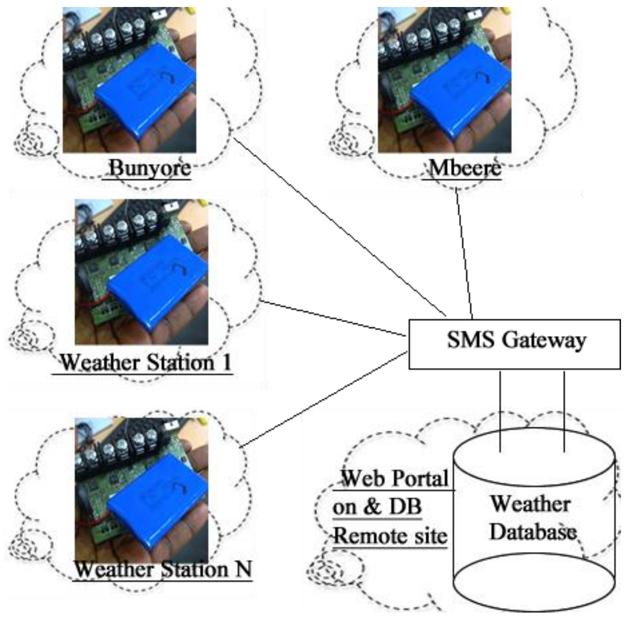


Figure 8-12: Wireless Sensor Boards

Program code that put into consideration the calibration weights reached at during the calibration exercise was loaded on to each of the sensor boards; readings were then taken every 30 minutes. To minimise the cost of sending SMS, the sensors send the readings to the database (using the GSM/GPRS module) via the SMS gateway on hourly basis. For backup purposes, each board also saves all (every 30 minutes) the readings in a SD card. The activity of the sensors is monitored from a web interface; a sample is shown below.

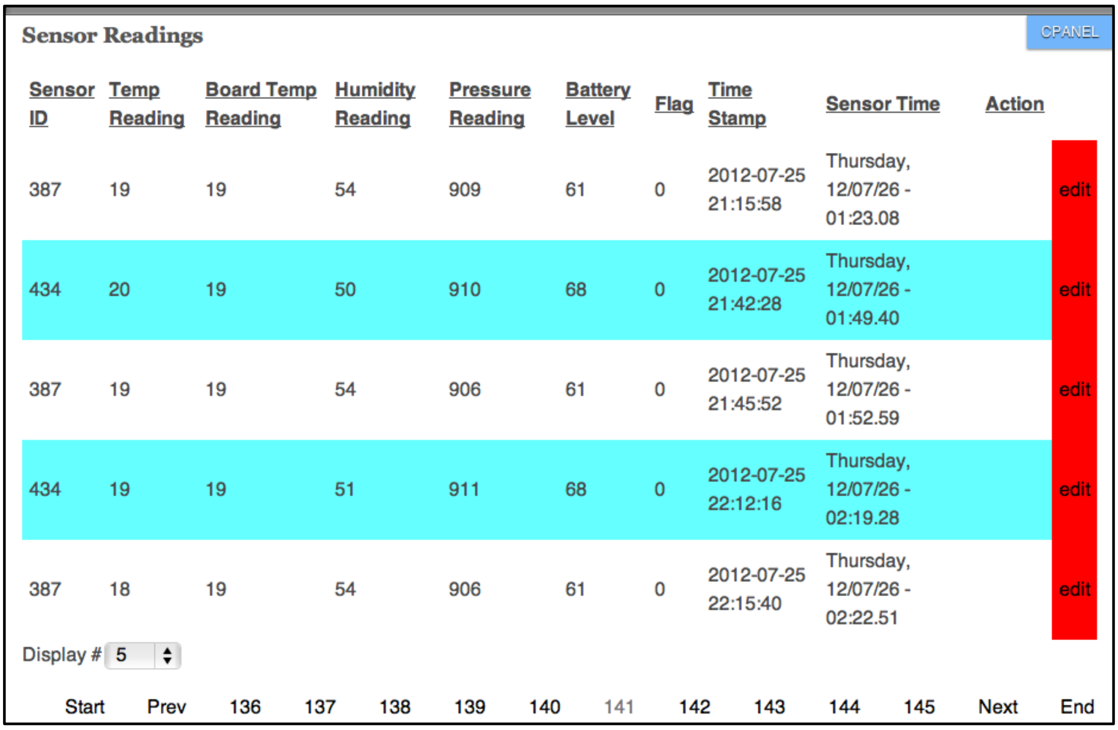
Sensors Monitoring Interface

All data from the sensors is accessible from the web portal from where the system administrator is able to monitor the sensors behaviour. Both textual (see figure 8-13) and graphical views are available. A sensor board that does not send readings for a period of one hour is deemed to have 'failed' due to either (or all) of the following reasons:

Depleted airtime: The SIM cards installed on the sensor boards were always topped up with adequate airtime for sending the weather readings in form of text messages. However, in isolated cases, the airtime got depleted and therefore such a sensor board would not send the readings. Simply topping up the SIM card remotely would solve this.

Low Battery Power: Based on the calibration results presented in Chapter 5; a sensor board's battery would be replaced (with a fully charged one) as soon as the *BatteryLevel* value was below 40%. However, there are situations where some boards failed long before the battery power level went below 50%.

Failure of the GPRS module: the GPRS installed on the sensor boards caused most of the failures; it would fail to connect to the network, causing the program code on the sensor to hang. This was the most difficult problem to solve because it required re-starting (reprogramming sometimes) the sensor boards and hence interfering with the synchronisation of the readings. This also meant that only a technical person (with the knowledge of programming the sensor boards) would solve this problem. For instance, any time the stand-alone sensors installed in Mbeere and Bunyore failed, they had to be physically delivered to the administrator to reset them; this would take at least a day.



Sensor Readings

CPANEL

Sensor ID	Temp Reading	Board Temp Reading	Humidity Reading	Pressure Reading	Battery Level	Flag	Time Stamp	Sensor Time	Action
387	19	19	54	909	61	0	2012-07-25 21:15:58	Thursday, 12/07/26 - 01:23.08	edit
434	20	19	50	910	68	0	2012-07-25 21:42:28	Thursday, 12/07/26 - 01:49.40	edit
387	19	19	54	906	61	0	2012-07-25 21:45:52	Thursday, 12/07/26 - 01:52.59	edit
434	19	19	51	911	68	0	2012-07-25 22:12:16	Thursday, 12/07/26 - 02:19.28	edit
387	18	19	54	906	61	0	2012-07-25 22:15:40	Thursday, 12/07/26 - 02:22.51	edit

Display # 5

Start Prev 136 137 138 139 140 141 142 143 144 145 Next End

Figure 8-13: Sensor Boards Monitoring Interface

Sample Output from the Sensors

The example below is of readings from temperature sensors installed on sensor boards installed in Mbeere. The readings were taken between 15 July and 16 July 2012

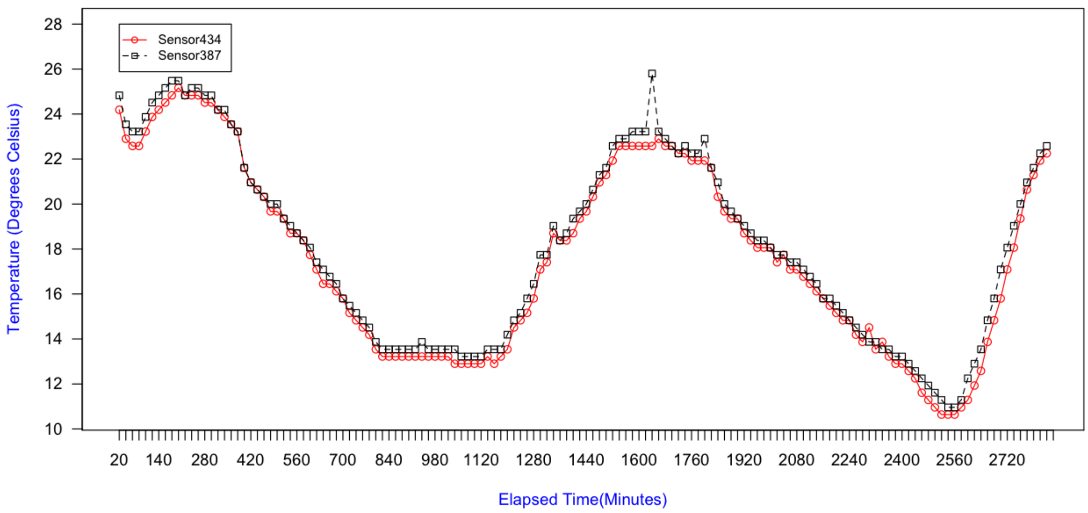


Figure 8-14: Sample Temperature Readings from Sensor Boards Located in Mbeere

Below are relative humidity readings from sensors located at KMD taken between 21 July and 25 July 2012.

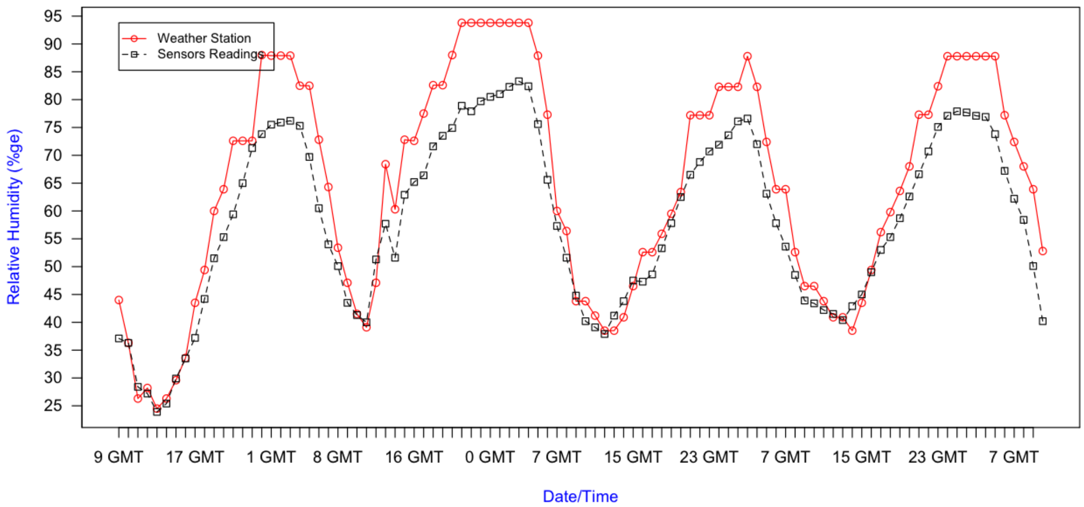


Figure 8-15: Sample Humidity Readings from Sensor Boards Located at KMD

The readings below show an example where one sensor stopped responding due to GPRS failure.

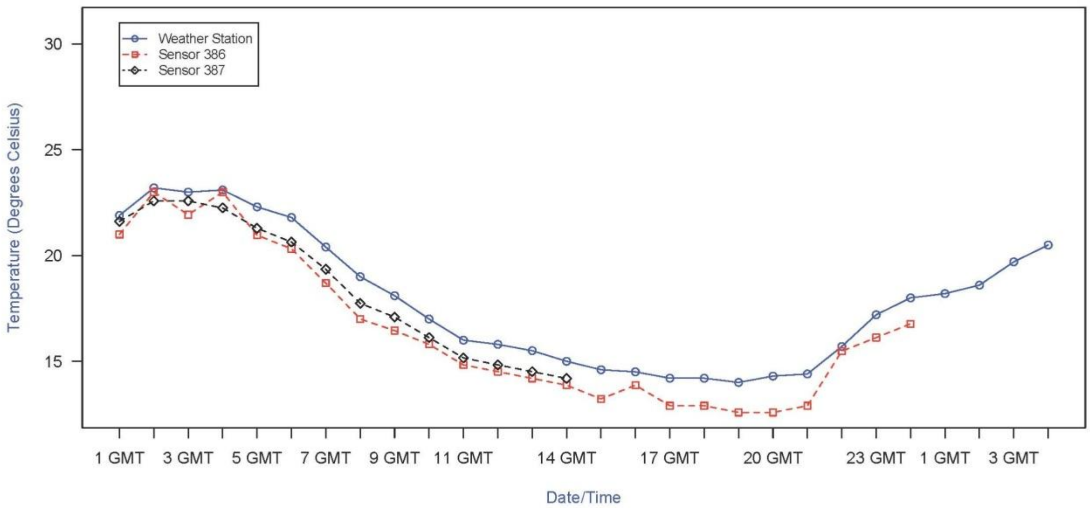


Figure 8-16: Sample Sensor Readings Showing a GPRS failure

8.2.4 Conventional Weather Station

Readings observed at the weather stations are captured into the database using the web from below.

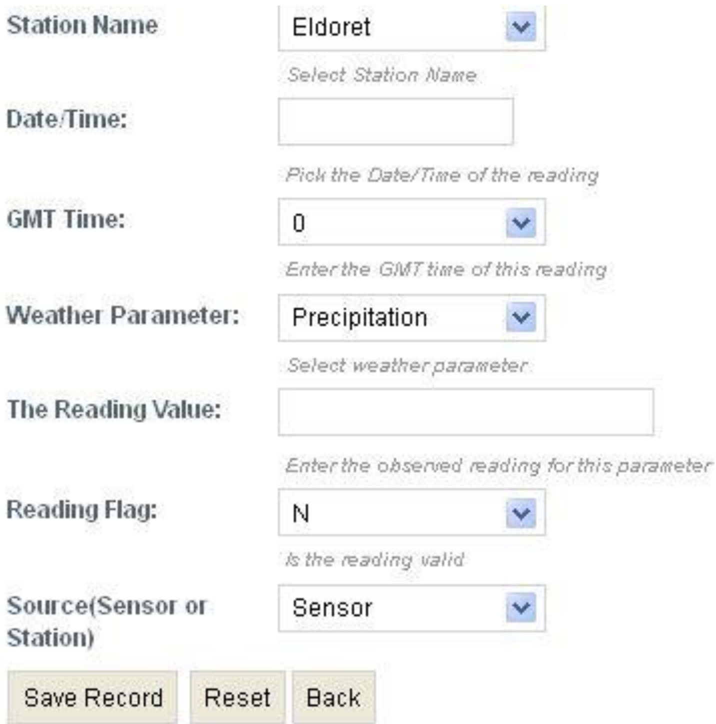


Figure 8-17: Weather Station Readings Capture Screen

8.2.5 SMS Gateway

This is a simple Java-based SMS Gateway made up of one main class (***SmsSender.java***); it is supported by two other classes; (***ComputerSmsData.java*** and ***SerialToGsm.java***) and one xml file (***configs.xml***). To have it run continuously, smsSender.java implements threads. It receives messages from the sensors, decodes them into the various components and then uploads the data to the database, which is located in a remote site. The SMS Gateway runs on a computer that is permanently connected to the Internet to allow for routing of the readings. It is currently installed in the Server Room in the School of Computing and Informatics, University of Nairobi, Kenya.

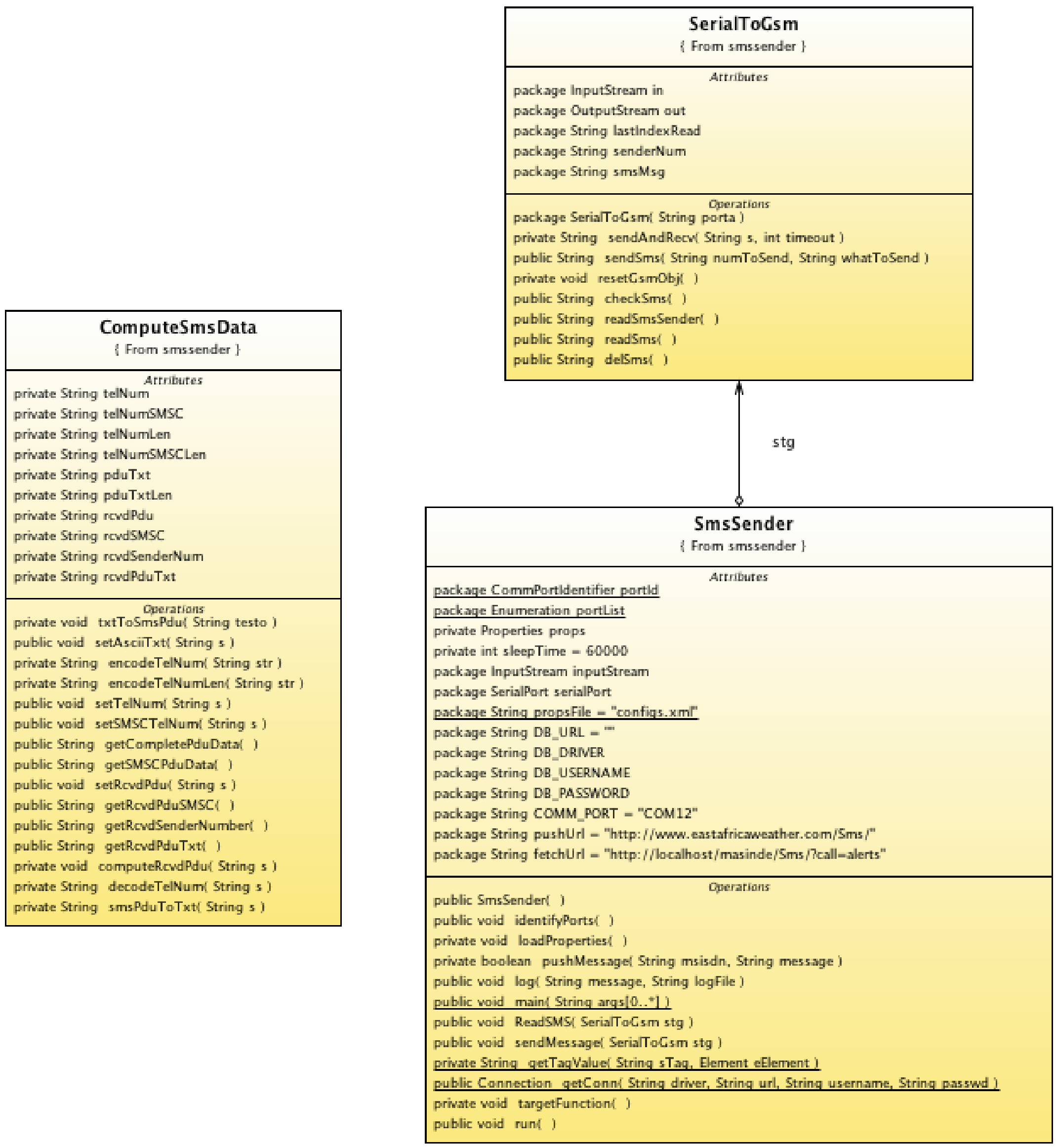


Figure 8-18: SMS Gateway – Class Diagram

8.2.6 Published Weather Reports

Since weather forecasting was not part of the DEWS described here, the various weather forecasts needed for various DEWS' decisions are currently retrieved from published weather reports. ***Seasonal Forecasts*** from KMD are retrieved from the website (www.meteo.go.ke) and used to populate the relevant database tables. ***Daily***, ***5-day*** and ***7-day weather forecasts*** (also from KMD) are used as input to the ANNs forecasting models. Some aspects of the Seasonal Forecasts that deal with advising stakeholders are incorporated in the IK Fuzzy System to enrich the disseminated forecasts. Finally, the ***10-day Dekad Reports*** are used to evaluate the extent to which the EDI monitor is able to quantify droughts.

8.3 System Layer 2 – Drought Monitoring and Prediction

8.3.1 System Layer 2 - Analysis

This layer consists of three components, which make use of the data collected in Layer 1 to monitor and predict droughts. The **EDI Monitor** generates EDI and AWRI values that are uploaded into the database; these values are then used by the ANNs models to predict future droughts. The ANNs Models achieve this by combining the values (EDI and AWRI) with the weather readings (current and forecasted). The IK Fuzzy Logic System makes use of the IK weather indicators, seasonal weather forecasts and drought (short and medium term) forecasts from the ANNs models to come up with IK-compatible drought forecasts.

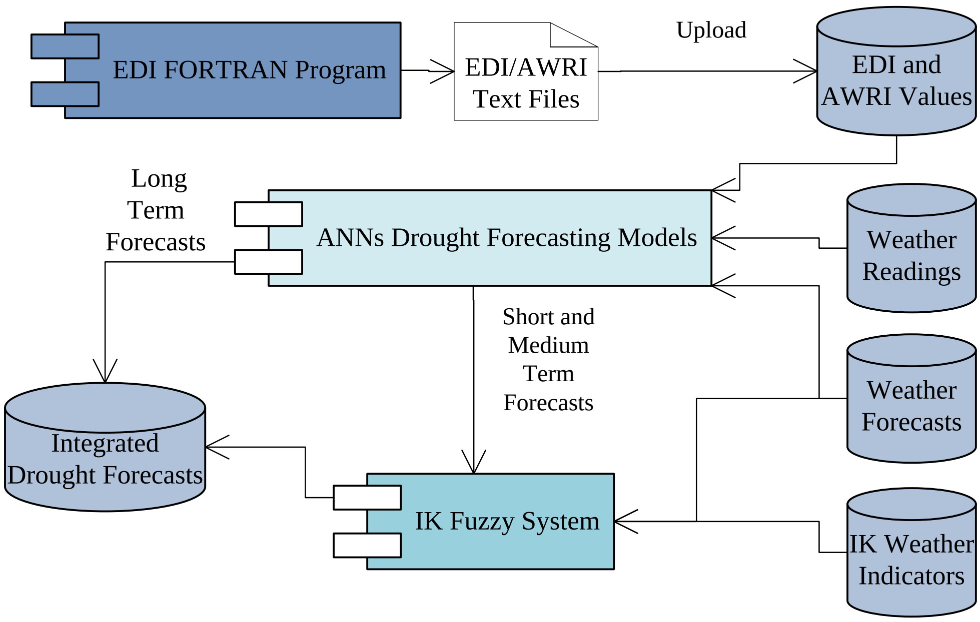


Figure 8-19 System Layer 1 Logic

8.3.2 EDI Web-Based Decision Support System

Using the daily precipitation, computed EDI/AWRI and Drought Classification, a web-based interface was implemented to demonstrate how EDI could aid in detecting and preparing for droughts/floods. ***Jpgraph-3.5*** was used to draw the dynamic (database-driven) graphs.

Presented with daily EDI values that are constantly rising (positive) and a seven-day weather forecast (say from KMD) that shows steady increase in the amount of rainfall, a decision maker can absolutely know when and how severe the coming floods will be. The figure below shows the main screen of the web-based interface; it allows users to select a weather station, year and month. The user can also opt to choose all years and/or month.

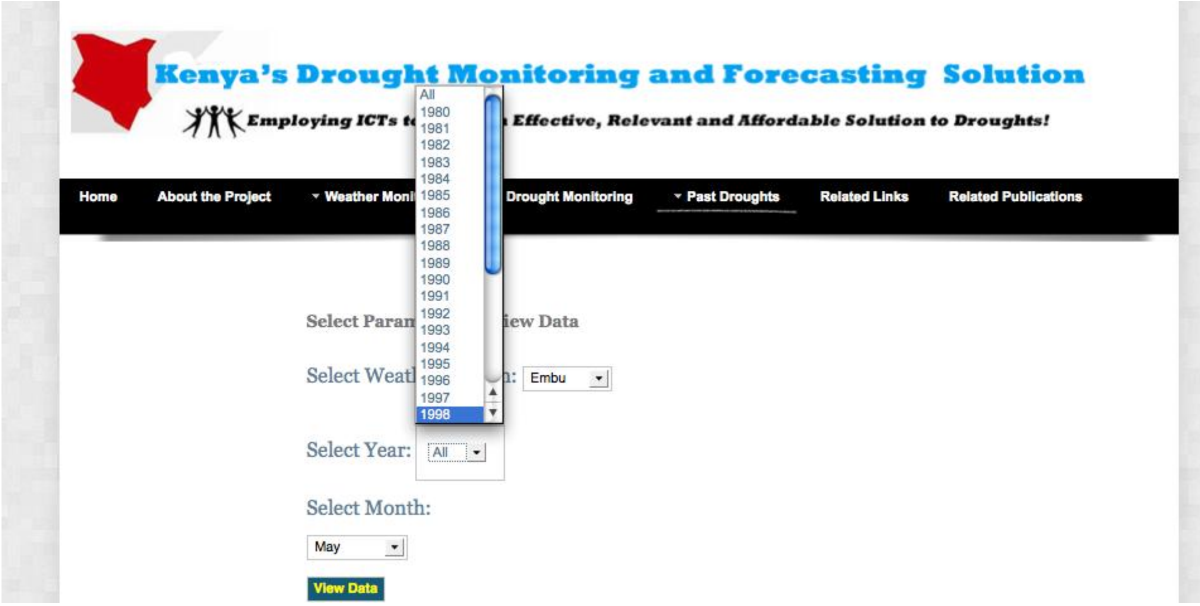


Figure 8-20: EDI System's Main Screen - Selecting Parameters

Drought Views

The objective of building this simple system was to provide a simple and easy to use user interface for visualising the historical droughts/floods. The following viewing options are currently supported by the system:

(a) One Month, One Year, One Station Data

Once the user has made selections and clicks 'View Data', for example, selecting Makindu, 2009 and May, the daily EDI values, AWRI Values and the Drought Classes are displayed as shown in Figure 8-21. In this case, May 2009 was a drought (Severe and Moderate) month.

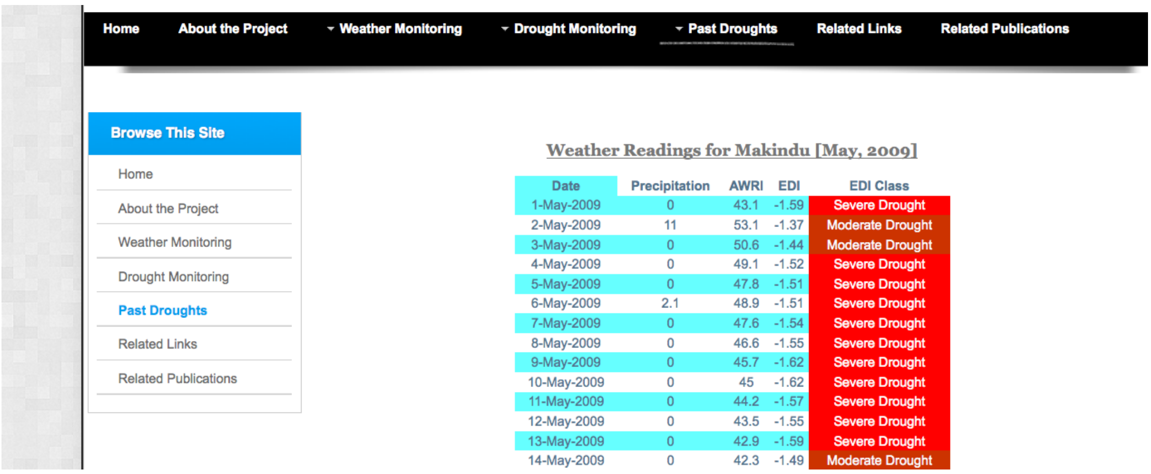


Figure 8-21: Sample View1 - EDI Values for Makindu, May-2009

(b) Multiple Years/Months

Views are also possible for a given month of all the years (say March 1980, March 1981,…, March 2009). These are displayed when a user selects one month say

March) and 'All' in the Year option. Similarly, selecting 'All' for month option and a given year (say 1998) will display daily values for January to December of the chosen year

(c) Graphical View

Users can opt to view graphs of the EDI values; these are useful in detecting trends that may lead to droughts/floods. By moving the mouse over bars, the user is able see the actual value of any bar. For example, in the figure below, the value for the bar corresponding to24 July 1998 is +2.78. Clicking on the any bar also opens a new window with more interpretations of the EDI value.

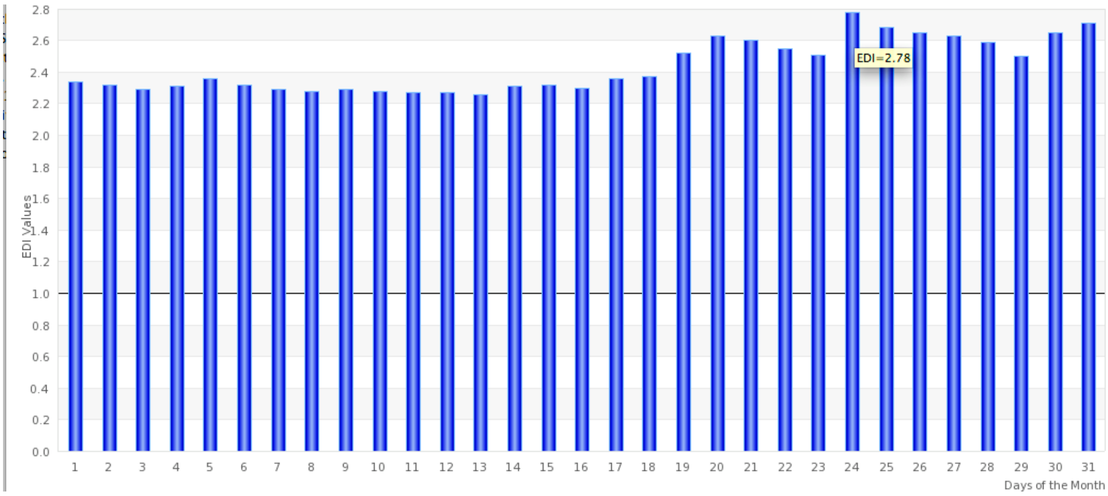


Figure 8-22: Sample View2 - EDI Graph for Embu, July 1998

It is easier to see a pattern in a graph than in a table of values. In the graph (where X-axis represents days of the month and 'Y-axis represents the EDI) above for example, the floods were getting worse in Embu as the rains continued to pound. Plotting graphs for a whole year (see below) can also be useful in quantifying past droughts/floods.

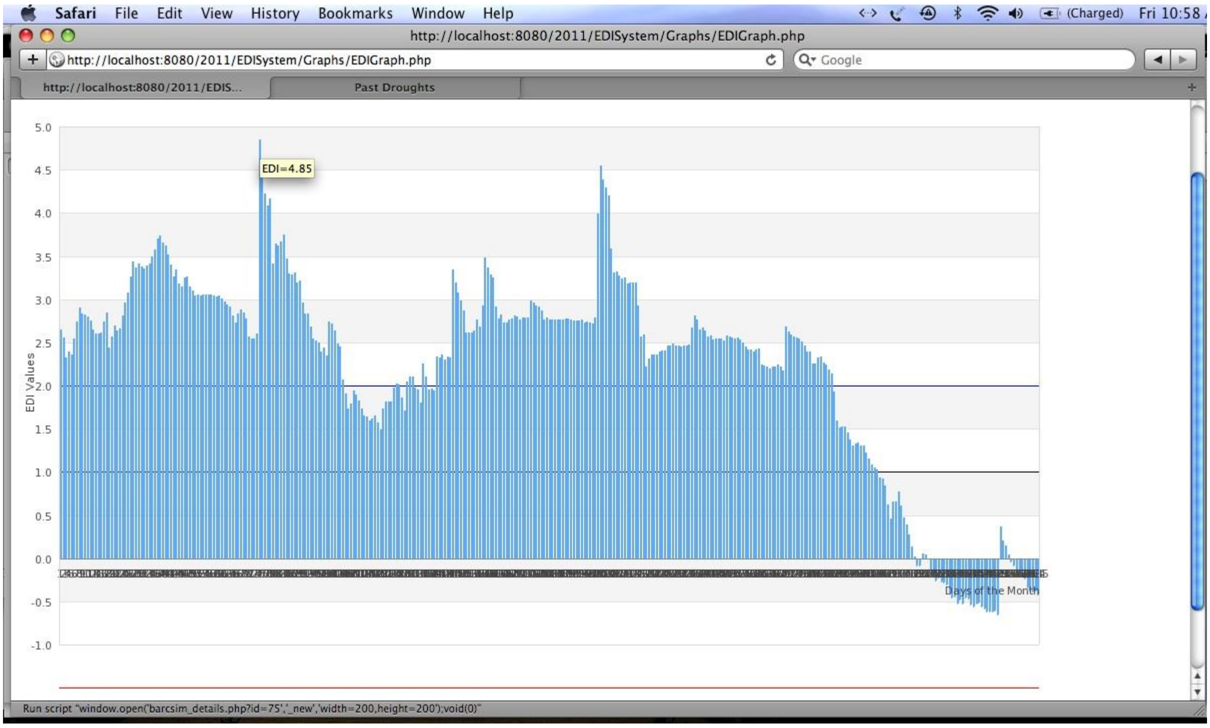


Figure 8-23: Sample View3 - EDI Values for Dagoretti, January-December, 1998

8.4 System Layer 3 – Drought Forecasts Dissemination

8.4.1 System Layer 1 - Analysis

A multi-agent system was created to link up all the DEWS' components after which the various output interfaces were created. This is made up of 3 types of agents; (1) Information Capture Agents, (2) Monitoring and Forecasting Agents, and (3) Dissemination/ Communication Agents.

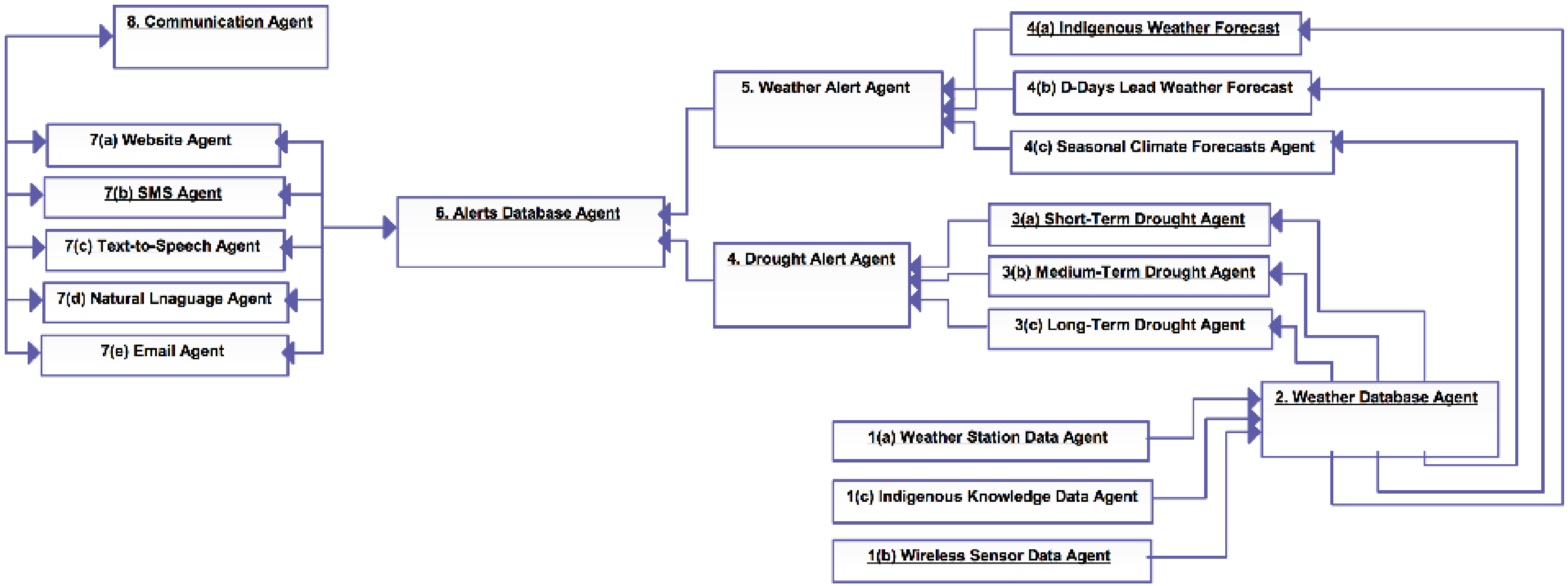


Figure 8-24: MAS - Collaboration Diagram

(a) Information Capture Agents

Weather Station Data Agent – 1(a) retrieves structured weather data from a MySQL Database; this is the weather station data manually entered via the web interface discussed under section 8.2.4.

Wireless Sensor Data Agent – 1(b) aggregates the half-hour sensors' readings from multiple sensors to come up with a single sensor reading. In cases where there is a weather station reading from the same locality as the sensor board(s), this Agent compares the two and reports the error value if any.

Indigenous Knowledge Data Agent –1(c) manages the data from the ***mobile phone application*** which consists of: (1) Weather indicator description, for example: "strong wind blowing out of Lake Victoria"; (2) Weather Indicator implication, for example: "it will rain in 2 weeks' time"; (3) Indicator Strength, this is an integer value ranging from 1 to 4. Level 4 implies '*very strong'* while 1 implies '*very weak'*.

Weather Database Agent – 2 is the storage for the data presented by agents 1 (a), 1(b) and 1(c). The agent later provides the data on-demand basis to the agents responsible for drought monitoring and forecasting.

(b) Monitoring and Forecasting Agents

These are responsible for monitoring/forecasting weather and droughts.

Droughts Agents: 3(a), 3(b) and 3(c) perform two tasks: (1) Retrieve historical drought indices (EDI and AWRI values) from an existing database; and (2) Use pre-defined Artificial Neural Network (ANNs) modes (created using MATLAB) and weather data from the Weather Database Agent to forecast droughts for short-term (Agent a), medium-term (Agent b) and long-term (Agent c)

Agent 3 (a) - Short Term Drought Forecast

The Agent receives a request for drought forecast N days ahead for Station S (say with ICAO HKEM); N ranges between 1 and 14 days. For instance, given N=5, the agent takes the current date (for example 17 April) and adds N to it; in this case 17 April + 5 days = 22 April. Using the latter date, the Agent interacts with ANNs models to retrieve the drought forecast.

Agent 3 (b) - Medium Term Drought Forecast

The Agent accepts a request for drought forecast for N months ahead. Here, N varies from 1 to 11. For example, if N=10 for Station HKEM, the agents adds 10 the current month (4 for April); April 2012 +11 months = February 2013. Using this (Feb 2013), the Agent retrieves drought value from the ANNs Models.

Agent (c) - Long Term Drought Forecast

Similarly, this Agent accepts value N and Station's ICAO; N varies from 1 to 4 years. On receiving N, say 2, the Agent adds N to the current year; 2012 + 2 = 2014. It then retrieves all 12-drought values (one for each month) for the Station provided for Year 2014 from the ANNs Modes.

Weather Agents – Agents: 4 (a), 4 (b) and 4 (c) retrieve weather forecasts already stored in the database and passes them to other Agents that need them.

Alerts Agents (Weather Alerts Agent and Drought Alert Agent) - based on the outputs from weather/drought forecasts, these two agents creates appropriate alerts and pass them to the Alerts Database Agent for storage.

(c) Dissemination Agents

These are agents 7(a) to 7(f) and they are responsible for converting the drought/weather alerts from the Alerts Database into various formats (email, sms, web content, etc). They then forward these to the Communication Agent, which acts as the interface with the end-users.

8.4.2 System Layer 3 Design

Database Design

Below is the database design for the integrated DEWS:

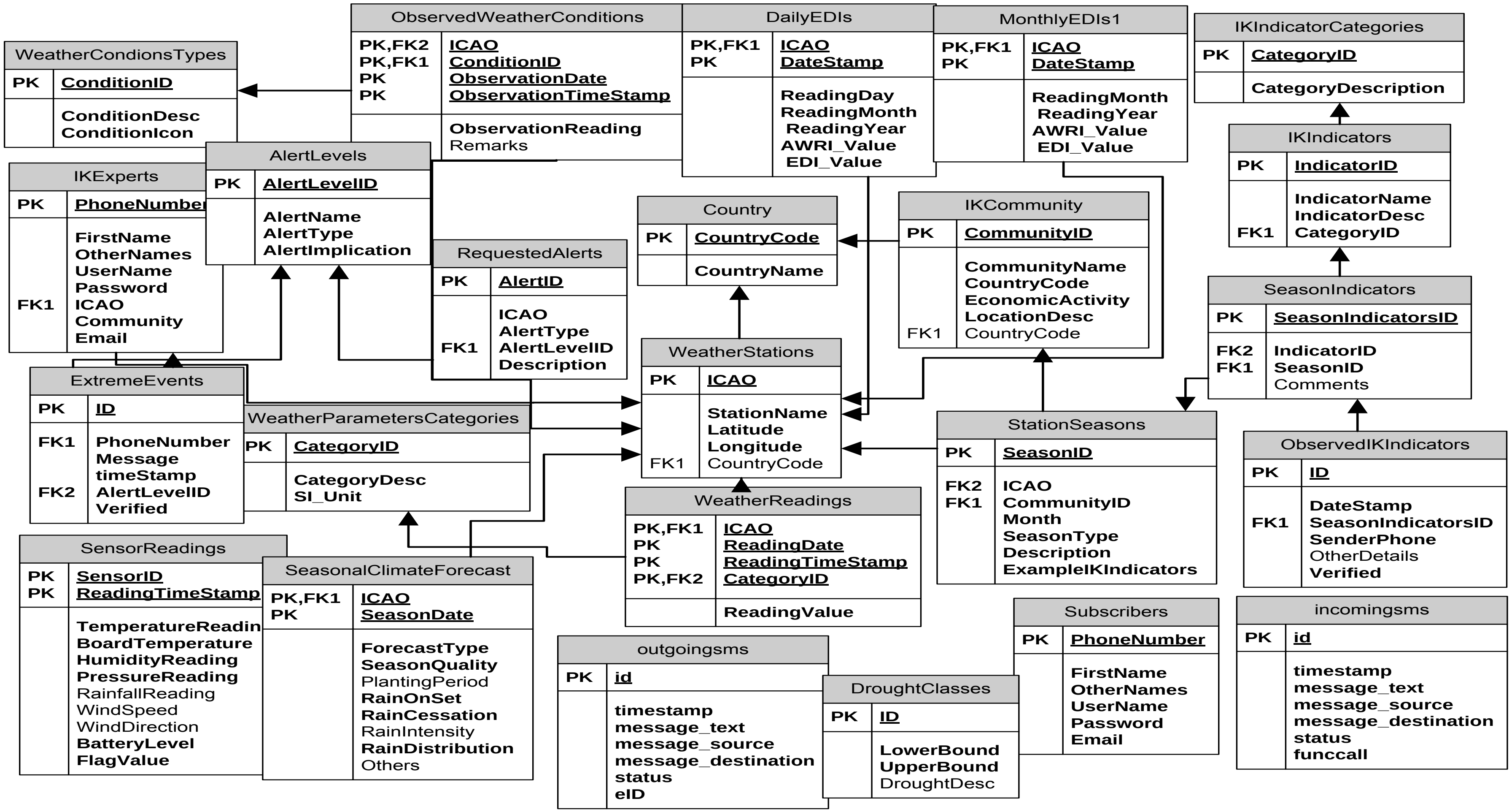


Figure 8-25 DEWS Entity Relationship Diagram

8.4.3 System Layer 3 - Implementation and Testing

Database

The database design above was physically implemented in MySQL database. The various integrity constraints were implemented as required and in cases where the entity relationship was too complex (as in the case of IK Indicators), stored queries and database triggers were used to visualise the data.

Multi Agents System

The Agents system ties together all subsystems; it was implemented in JADE as using a set of 12 packages shown below.

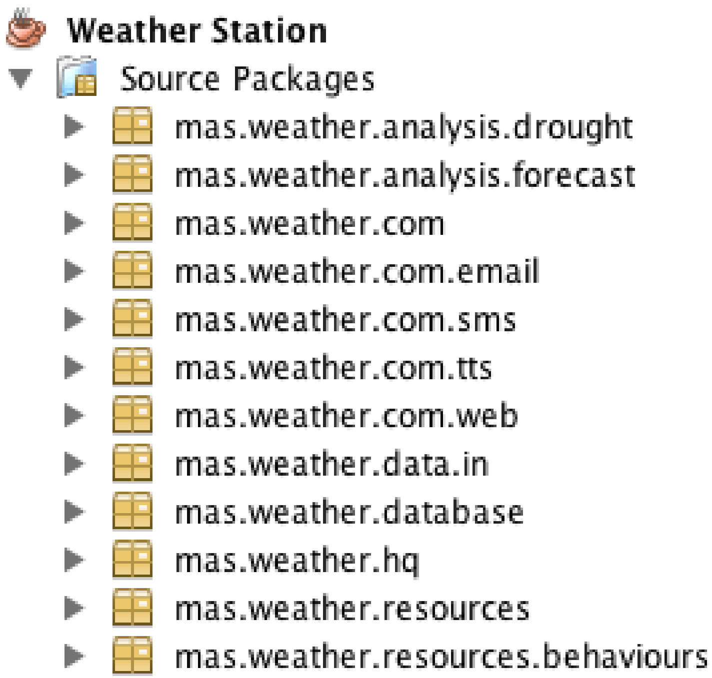


Figure 8-26 MAS Implementation Packages

Testing

(a) Drought Forecast Via SMS

The system accepts requests in form of text messages (sms) in the format:

<Df>;<Weather Station>;<ForecastType>;<Lead-Time>;

Df – for Drought Forecast; Weather Station – represented by ICAO; ForecastType – either Short Term (1), Medium Term (2) or Long Term 3); Lead-Time – ranging from 1 to 14 days for Short Term, 1 to 12 months for Medium Term and 1 to 4 years for Long Term

Example: Df;HKEM;2,2 - A request for Medium-Term Drought for Embu weather station for two months lead time.

Figure 8-27: Medium Term Drought Forecast – SMS

(b) Agents Interaction

The AlertsDatabaseAgent continuously checks for any incoming SMS with 'Df' (for drought forecast) keyword. Once a message is found, this Agent decodes the various parts of the message including the sender details. The latter are later used by the EmailAgent to send a copy of the requested forecast to the sender's email address. Once the respective forecasting agents are invoked, they in turn call EmailAgent, SMSAgent and Audio Agent for output purposes. In the current implementation, both the Short-Term-Drought-Agent and Medium-Term-Drought-Agent invokes the Indigenous-Knowledge-Agent to be able to integrate the IK aspect of the forecast in the response sent to the user.

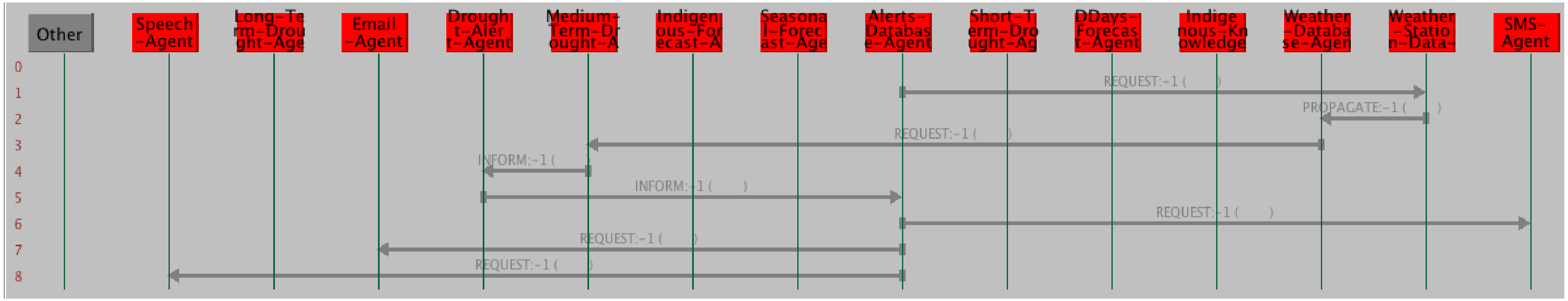


Figure 8-28: Medium Term Interaction Diagram

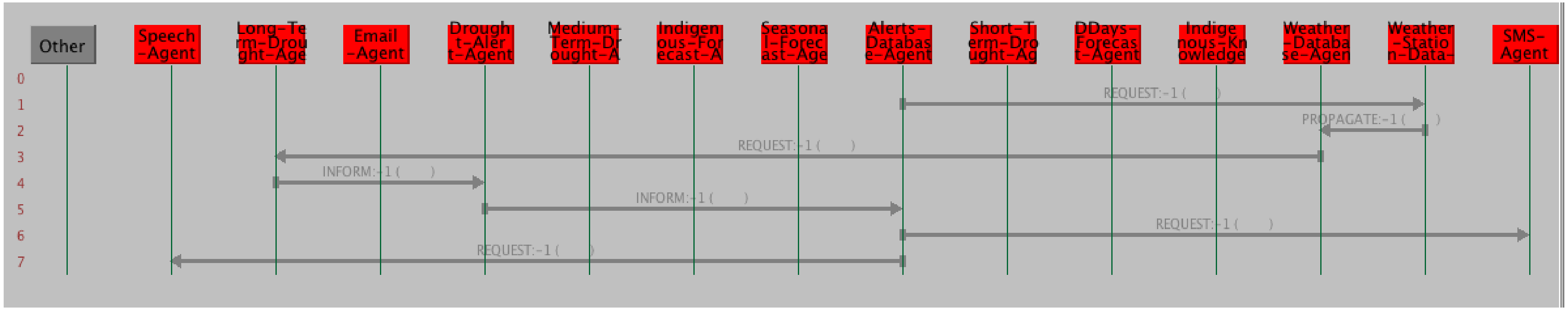


Figure 8-29: Long Term Interaction Diagram

(c) Email Output

For each of the requests received, the EmailAgent sends a copy of the drought forecast to the sender. The Agents interacts with the WeatherDatabaseAgent to retrieve the email address of the SMS sender; an email is then sent to this email address.

Figure 8-30: Medium Tem Drought Forecast - Email

(d) Audio Output

For each of the drought forecast, the SpeechAgent generates an audio version and stores it on the remote site. The link to the file is stored in the database table, alertsTable and is available for download via the web portal. For instance, the requests above are stored in the paths:

audio/Drought/HKEM/2012-8.wav – representing the audio file for the medium-term drought forecast for Embu for August, 2012

(e) Web Portal

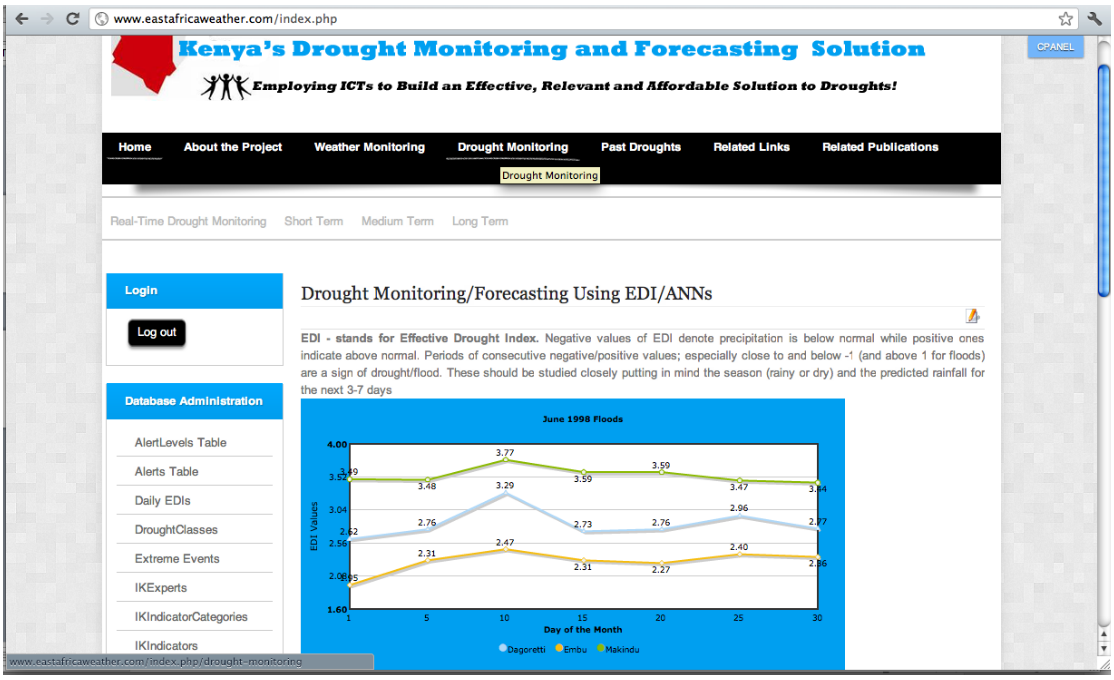


Figure 8-31: Web Portal Home Page

Web Portal Functionalities

All the functionalities of the integrated DEWS are accessible from the web portal. Examples include:

Real-Time Weather – to check the most current weather for a given location; this displays readings from both the weather station (if any) and sensor boards

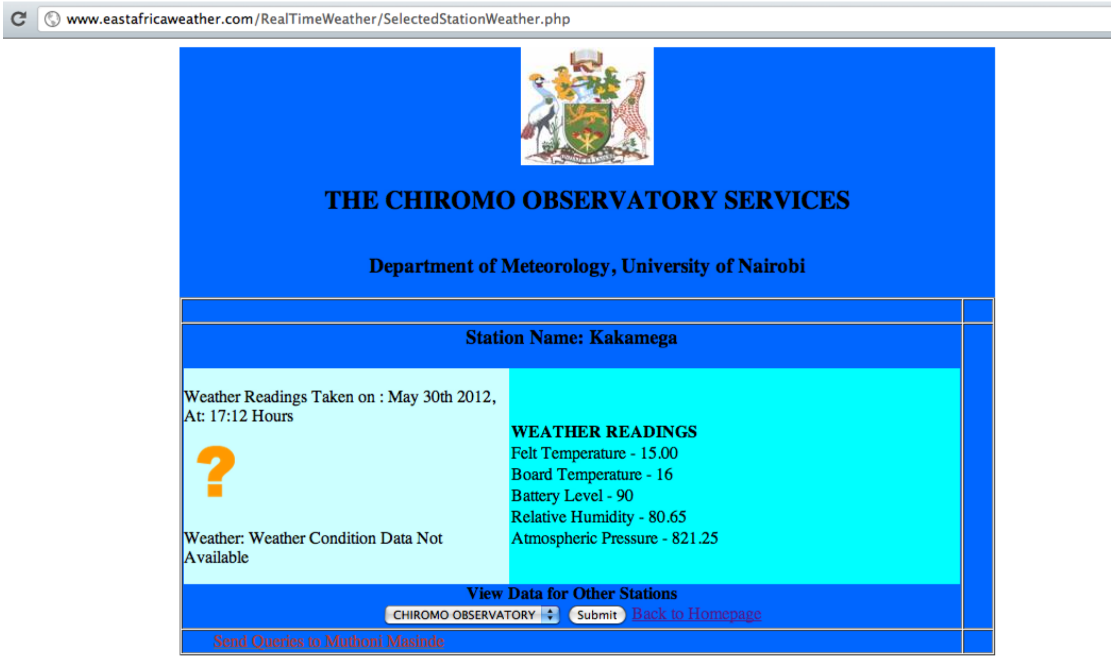


Figure 8-32: Real-Time Weather Webpage

Drought Monitoring that supports short, medium and long-term drought forecasts as discussed under Agents

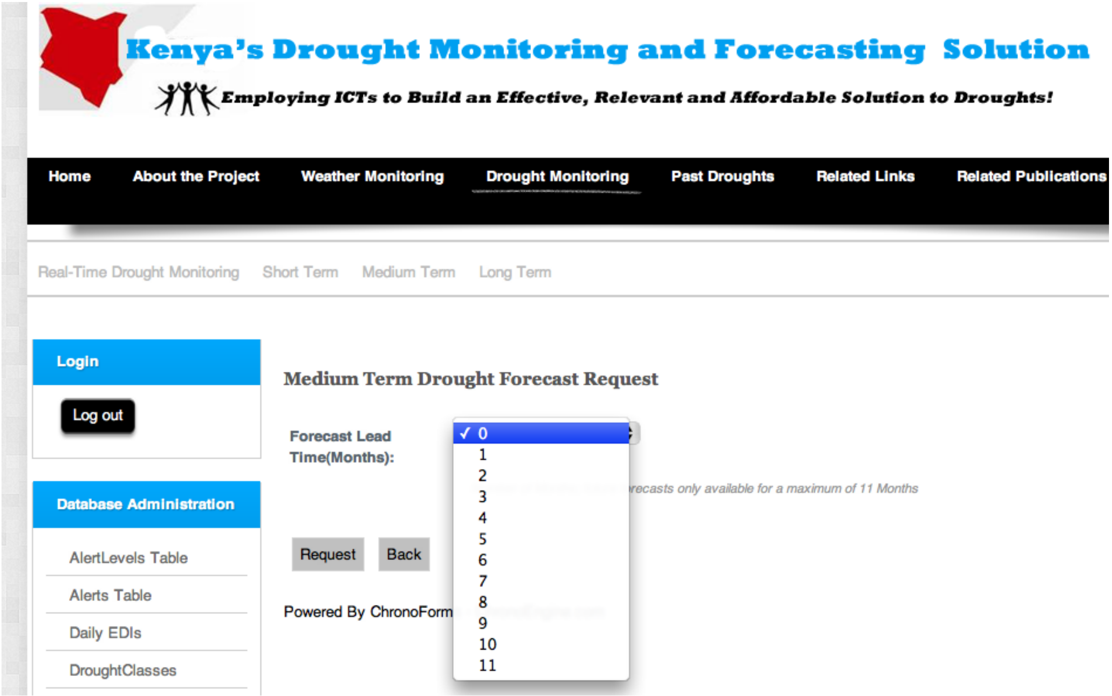


Figure 8-33: Medium Term Drought Forecast Webpage - Request

Selecting 2 (for 2 months) yields the results below:

Medium Term Drought Forecast: Aug-2012

Counter	Station Name	Month-Year	Precipitation	AWRI Value	EDI Value	Drought Descrption
1.	Embu	Aug-2012	50	8	-1.3	Moderate Drought
2.	Nairobi / Dagoretti	Aug-2012	10	900	-1.7	Severe Drought
3.	Lodwar	Aug-2012	0	70	-2.1	Extreme Drought
4.	CHIROMO OBSERVATORY	Aug-2012	9	809	0	Drought-Near Normal
5.	Kakamega	Aug-2012	90	1020	1.8	Severe Flood

Figure 8-34: Medium Term Drought Forecast Webpage – Results

System Administration

The web portal also supports all the system administration functionalities such as database records manipulation (add, delete and update). This is implemented in form of menu accessible system administrators only.

Browse the Database

For most of the tables in the database, a public view of the data is provided via the menu 'Browse Database'.

9. Evaluation, Discussion and Conclusion

9.0 Introduction

This chapter gives a summary of the extent to which the objectives that were set out in Chapter 1 were achieved. This measure is presented in form of various benchmarks that were used to measure the achievements. The discussion, further work overall conclusion of this research is in section 9.4.are also presented here.

9.1 Evaluation

9.1.1 Objective 1: WSNs for Drought Monitoring

As described in Chapter 5, agriculture sensor boards from Libelium were found to be more appropriate because unlike others that we evaluated, these boards are open and support sensors for sensing among many other parameters: (1) precipitation; (2) surface air temperature; (3) atmospheric pressure; (4) wind direction and speed; (5) relative humidity and (6) soil moisture. In order to evaluate the objective on the suitability of these sensors as a complementary technology for the sparse network of weather stations found in SSA, a prototype weather monitoring system was set up. This was preceded by a rigorous sensor calibration exercise geared towards evaluating the sensors' field-readiness and their acceptability by meteorologists. This entailed comparing the sensor boards with the conventional weather stations run by KMD. Readings from both the sensors and the weather stations were taken in parallel 24 hours a day, for a period of six months and Regression Analysis, MAPE and RMSE analyse sensors' error rates. The sensors' readings had impressive accuracies ranging from 92 to 99 %. Post calibration readings taken from the sensor boards deployed in the field maintained these accuracies.

Other aspects of the sensor boards that were evaluated were sensors' lags errors, GPRS response time, battery depletion rates and effects of putting sensors in a protective (from the environment) enclosure. Though still experiencing some minor problems that are explained in the Further Work section, WSNs technology proved to be a viable technology for complementing the sparse network of weather stations found in SSA. The weather monitoring system prototype installed was still up and running in Kenya at the time (October 2012) when this thesis was written.

9.1.2 Objective 2: Mobile Phones for Drought Monitoring

In an effort to extend the functionality of mobile phones into computing devices that can be used in drought prediction, grid computing and service oriented computing (SOC) paradigms were experimented. We developed and tested MobiGrid (Masinde, Bagula et al. 2010); this is a novel middleware for mobile phone grid. The concept of using SOC on mobile phones was implemented and tested using a mobile-based questionnaire **(**Masinde, Zebal et al. 2012). Overall, we were able to evaluate the possibility of using mobile phones as computing devices in the developing countries of Africa where there penetration of phones is much higher than that of computers.

9.1.3 Objective 3: EDI for Drought Monitoring

World over, droughts are quantified/qualified using drought indices; for reasons described in Chapter 2 and Chapter 6 we settled on EDI for this research. Before embarking on the development of the DEWS that uses EDI, we used daily weather data for over 30 years for four weather stations in Kenya to evaluate EDI's performance and suitability for monitoring droughts. EDI was able to quantify and qualify in absolute terms of two major events (the 1983-85 drought and 1997-98 floods) in Kenya using five dimensions: onset, severity, duration, termination, and probability of future occurrence.

For example, we used EDI to piece together the following details about the *onset*, *severity*, *duration* and *termination* of the 1998 floods that hit most parts of Kenya.

"The October-November-December 1997 torrential rains triggered the floods. This was later worsened by the March-April-May 1998 rains. At some point, the floods were so severe; for example, over 100mm of rainfall was recorded on 11 February 1998 in Makindu; February is generally a dry month so this put the EDI at a catastrophic value of +5.27. Similarly, a way above normal rainfall measuring 167.7mm was recorded in Dagoretti on 16 March 1998. Given that it had been raining and the ARWI was already at 303.3, this rainfall just turned things inside out and resulted in a dangerous EDI value of +4.85".

Such detailed information on droughts/floods was only possible with EDI. More of these is analysed in Tables 6-8 and 6-9. Further, though yet to be fully verified, we also used EDI to reach the hypothesis that an extreme drought/flood during the October-November-December season is likely to remain or worsen during the March-April-May season.

9.1.4 Objective 4: IK and Drought Monitoring

Despite the challenges encountered in acquiring information regarding IK on drought/weather forecasting, a breakthrough was made from the rigorous literature review and the case study of the Mbeere and Abanyole people in Kenya. From this, an intelligent system framework and prototype based on Fuzzy Logic was developed; this retains IK's holistic nature that is the source of its (IK) complexity. Clear classification and/or generalisation of rain seasons were completely avoided in favour of imprecise terminologies such as *favourable season*, *poor harvest*, *good production* and so on. The design and implementation of our DEWS' database and web portal further extended this holism, making the system able to output holistic answers such as "*the rainfall will be 'enough' to sustain a particular kind of crop, on a given piece of land when planted at a particular period*".

To prepare for the case study for the integrated DEWS; an android mobile phone application was developed and tested. The application is designed to work even in places where there is no or limited Internet connection. Further, in order to eradicate incorrect/imprecise IK, the application was designed to work within a focus group and IK weather/drought indicators are only passed to the system after a consensus among the IK 'experts' within the given community/region. The mobile application has been in use since June 2012 and the observed IK weather indicators continue to enrich our DEWS.

The effectiveness of this system was evaluated between September and October 2012 to forecast the onset of the October-November-December 2012 season. The Seasonal Climate Forecasts (SCFs) released by the Kenya Meteorological Department (KMD) indicated that the rains onset for Embu (the KMD forecasting region under which Mbeere falls) was between 2nd and 3rd week of October 2012. On the other hand, the IK forecast groups formed in Mbeere had been collecting IK indicators from July 2012. One of the strongest indicators reported was the behaviour of dragon fly which was interpreted to mean that the onset of rains was around 10th October 2012. Discussions were held to analyse the two forecasts (IK and SCFs) and necessary advisory issued. The IK forecast turned out to be more accurate because the rains did fall on October 10 2012 in most places in Mbeere. However, as discussed earlier in this thesis, this does not in any way mean that the SFCs were wrong but the sparse data used gave a bigger picture of the larger Embu Region which may not have adequately represented Mbeere

9.1.5 Objective 5: Drought Prediction

Overview

Most of the drought indices applied in forecasting droughts in SSA fall short of providing the severity of the drought. In addressing this drawback, we adopted a combination of Artificial Neural Networks (ANNs) and Effective Drought Index (EDI); this was evaluated by developing forecasting models for time-scales ranging from one day to 4 years. The models were then tested using weather data for over 30 years for 4 weather stations in Kenya. By including forecasted precipitation values as inputs to the ANNs models, our solution took care of the effects of unprecedented climate variations. It also exploited the correlation among EDI values of calendar months to forecast annual droughts. With accuracies raging from 75% to 98%, our solution is a great enhancement to the solutions currently in use in SSA.

ANNs Models Implementation and Evaluation

Artificial neural network as implemented in MATLAB's Neural Network Toolbox was used to develop drought prediction models discussed in Chapter 7. Extensive experiments were first carried out to determine the model input for the networks; this was done by varying combinations of Precipitation (P), Effective Drought Index (EDI), Available Water Resource Index (AWRI) values.

The ANNs models developed accepts as input a combination of EDI/AWRI and precipitation values and generate a set of EDI/AWRI values representing predicted drought.

For example,

A 2-Years Lead-Time (2 years in advance) Forecasting model could be used to forecast the 1998 floods a follows

$Forecast[E_{January,\ 1998}] = f\ (E_{January,\ 1996}, E_{January,\ 1995}, , E_{January,\ 1994}, , E_{January,\ 1993}, , E_{January,\ 1992}, E_{January,\ 1991}, P_{1991}, P_{1992}, P_{1993}, P_{1994}, , P_{1995}, , P_{1996}, , P_{1997}, , P_{1998})$

To forecast EDI values for January 1998, the neural network requires the EDI values for January 91, 92, 93, 94, 95 and 96. It also requires the annual precipitation totals for these years as well as an approximate annual precipitation value for year 1997 and 1998. Values for other calendar months are computed in a similar version.

That is, given 6 EDI and Precipitation values for 6 years and predicted precipitation values for the lead period (1997 and 1998), the ANNs model for 2-years lead-time outputs the EDI values (F_i) for 1998. The accuracy of this value (F_i) was determined by its closeness to the actual drought value (A_i) for this period (1998). Below is a sample plot of such relationships as generated by the ANNs model for 2-yeras lead-time for the period **October 1997** to **September 1999** using data for Makindu weather station data.

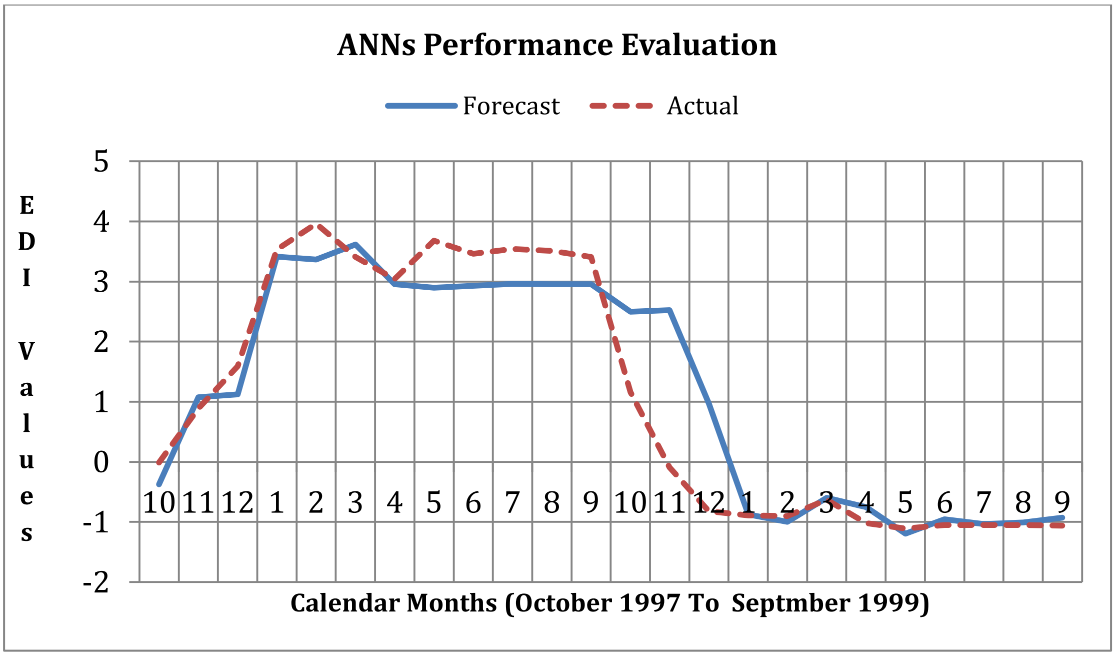


Figure 9-1: ANNs Evaluation – Predicted Vs. Actual Values Sample Graph

Mean Square Error (MSE) was then used to determine the accuracy of the forecasts. The '*best'* performance was retrieved from the MATLAB Artificial Neural Network Toolkit as illustrated in Figure 9-2 below.

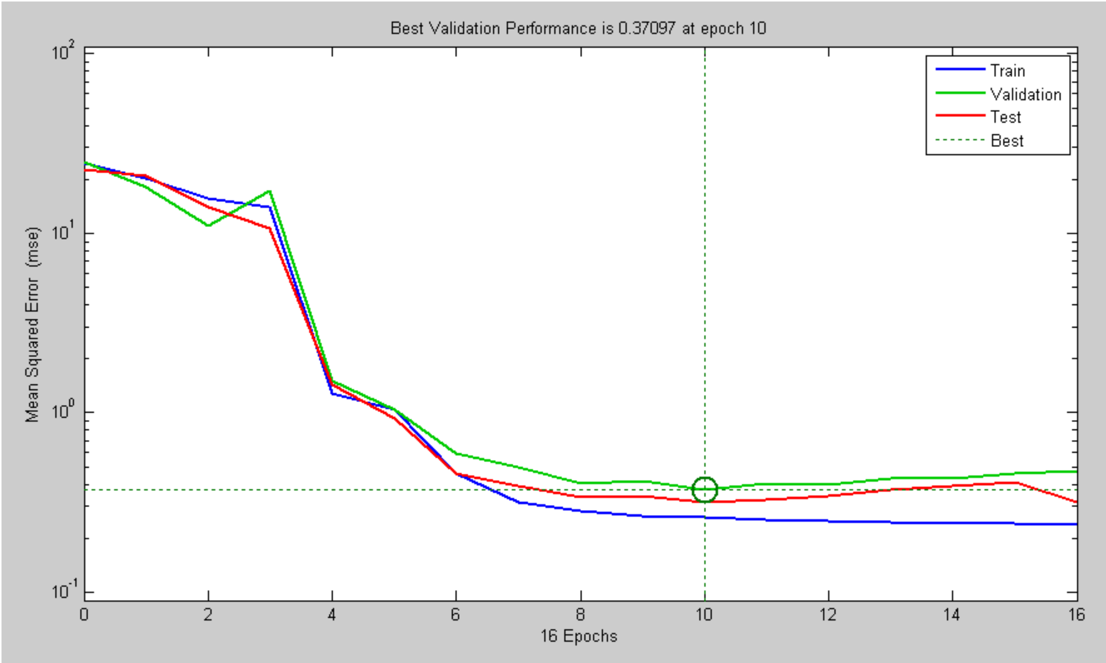


Figure 9-2: ANNs Evaluation – 'Best' MSE Sample Graph

In the case of 2-Years lead-time EDI forecast model for Makindu, the best performance (***MSE=0.37097***) was attained after 16 epochs[18].

Throughout our experiments, we used *validation error* to evaluate the performance of our network models. For instance, the data for Makindu for Y-Years Lead Time category (see Table 7-13) had MSE values of 0.205, 0.233, 0.267 and 0.270 for 1, 2, 3 and 4 years lead times respectively. The AWRI models for Makindu for the same network category gave values ranging from 3,037 to 4,661 (see Table 7-14). In order to put the MSE values into perspective, we further computed the Percentage RMSE which was easier to understand than the MSE. A value of 2.89% implied that the network had an accuracy of 97.11%. This analysis was performed for all models discussed in Chapter 7 and networks with accuracies of over 70% were considered acceptable.

To further evaluate the closeness of the F_i and A_i, regression analysis (see Figure 9-3 below) was used. Networks with correlation values of 0.9 and above were considered acceptable.

[18] The presentation of the entire training set to the neural network

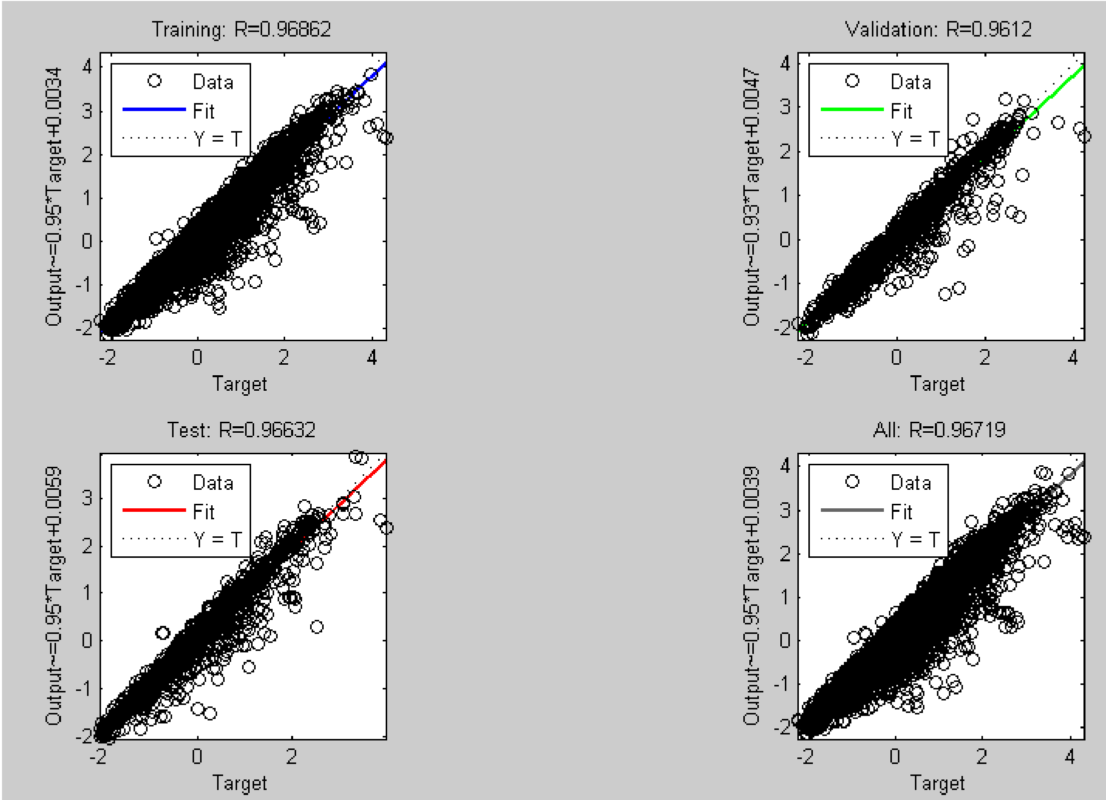


Figure 9-3: ANNs Evaluation – Regression Analysis Sample Graph

During the training of the ANNs modes, the conventional data division criterion for training, validation and testing sets was followed. During ANNs verification phase as described in Chapter 7, larger data sets not encountered by the trained network models were used to further evaluate the models.

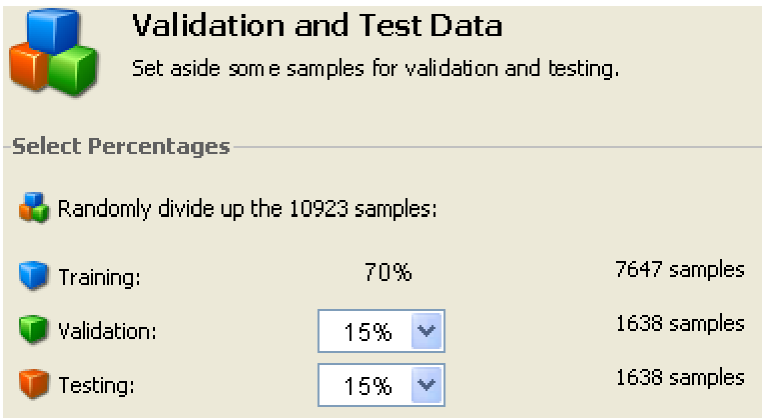


Figure 9-4: ANNs Evaluation – Validation and Test Data Sets

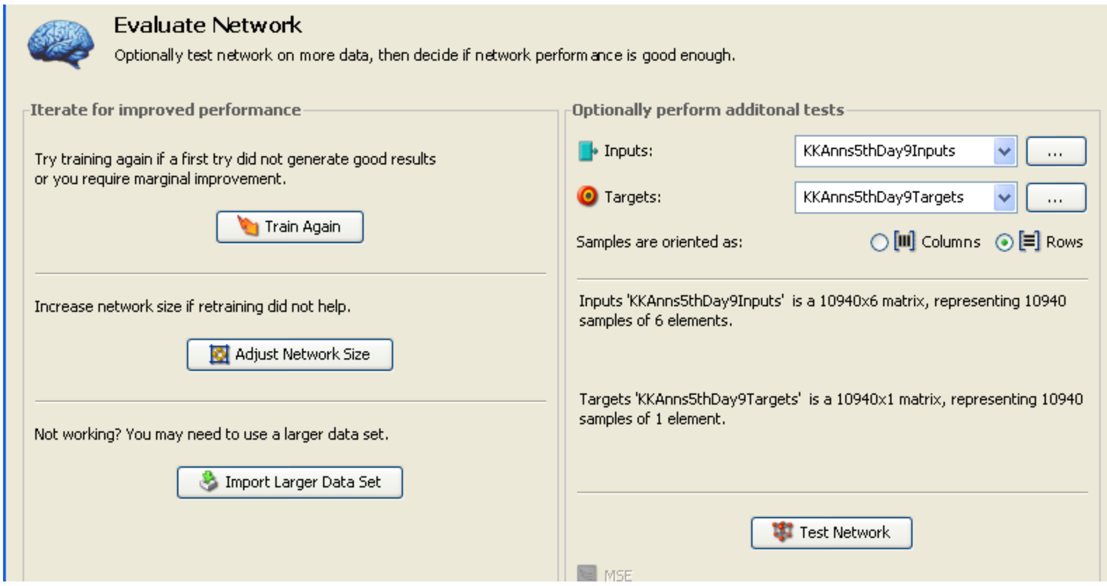


Figure 9-5: ANNs Evaluation – Independent Larger Data Sets

9.1.6 Integrated DEWS Evaluation

Guided interviews accompanied as well as demonstrations of the integrated DEWS prototype were carried out among the Mbeere and Abanyole communities in Kenya. An intermediary from the community approached the respondents (the same ones that were involved in the surveys described in Chapter 5) individually and gave a demonstration of the system features. Some demonstrations were run from the mobile phones application while others were based on printed system screenshots. Based on the content and format of the integrated forecasts, the respondents were asked to rank the system using a scale of 1(poor) to 3(excellent). 90% and 88% of the Mbeere's and Abanyole's respondents respectively, gave rankings of 3.

After explaining how the focus groups for the system deployment would work, respondents were asked if they would be willing to join these focus groups. Those who gave a YES response were requested to show their commitment by providing their names, phone numbers and national identification numbers. Again, 90% and 88% of the Mbeere's and Abanyole's respondents respectively registered their details; that is all those that found the system output to be excellent wanted to get involved in its implementation.

As mentioned in section 9.1.4, the system prototype was being piloted (at the time of writing this thesis) among the Mbeere people in Kenya. The first evaluation was for integrated forecast for the October-November-December 2012 rain season. The

SFC by KMD was enhanced using our ANNs forecasts for 1, 2 and 3 months lead-times and the resulting forecasts translated to Kimbeere language. This was disseminated among the members of the forecast groups in Mbeere. The various IK indicators observed in the period between June and early October were discussed and compared with the SFC and the reconciled forecasts were input into the system. The ability of our ITIKI to integrate these two diverse forecasts was therefore evaluated and proven to work.

9.2 Discussion, Conclusion and Further Work

9.2.1 Discussion and Conclusion

Despite challenges that were encountered during this research, several novel achievements and contributions were made to the body of knowledge. Droughts are a challenge in SSA and ours are steps in the right direction towards sustainable, relevant and effective drought monitoring solution. One of the major hindrances to effective drought prediction in SSA emanates from poor coverage by the costly to acquire and expensive to maintain weather stations. To address this, we successfully demonstrated that the more cost effective and sustainable sensor based weather stations could be used to complement the weather stations.

The existing systems of generating and disseminating drought forecasts are the source of the second problem; the information does not reach the most critical audience (small-scale farmers) and when it does, the information is incomprehensible to them. This we addressed by first incorporating the rich and holistic indigenous knowledge that the farmers are not only conversant with but it addresses their local contexts and have always worked for them. In order to reach the farmers where they are and in the language they understand, the use of mobile phones as input and output device was adopted. Speech-to-text and text-to-speech add-ons were incorporated to aid in input and output respectively. Future extensions to this aspect of the system are to include a tool to translate the forecasts into the local languages that the farmers understand better. This is currently manually carried out and posted on our research web portal. At the grassroots level, the translations are currently performed by an intermediary from the participating communities. Further, displays of critical drought/weather information on strategically located digital billboards could be implemented.

Our overall solution to these problems was encapsulated in our novel integrated drought early warning system called itiki. Itiki is first an acronym for **I**nformation **T**echnology and **I**ndigenous **K**nowledge with **I**ntelligence. Secondly, itiki is used among the Mbeere people (in Eastern part of Kenya) to refer to an indigenous bridge used until late 90s to go across rivers. The resilience of this bridge in relation to their modern bridges counterparts motivated the naming of our drought solution. Using this analogy, the DEWS presented in this work took the form of a bridge that provides the much-needed link between the scientific and indigenous drought forecasting approaches. The raw material for our bridge is ICTs; in particular, WSNs and mobile phones. Artificial Intelligence technologies were used to glue these diverse components into an intelligent, integrated early warning system for droughts.

We acknowledge that predicting droughts alone cannot eradicate droughts in SSA; access to relevant and accurate information on impending droughts in timely fashion and comprehensible formats however could go a long way in assisting all the stakeholders plan for and mitigate effects of the droughts. This precisely is the contribution of *itiki*. The presence of sensors in *itiki* enables capture of micro weather data and hence, improved prediction accuracy. Indigenous knowledge on the other hand helps in improving relevance (culturally and locally), acceptability and sense of ownership of the forecasts among the small-scale farmers. The systematic capture and storage of IK on weather that we implemented is a phenomenal step towards the much needed conservation of the endangered IK.

9.2.2 Further Work

Our DEWS is a prototype with lots of extensions in-waiting as described below:

Drought Knowledge Component; first, more sensor boards need to be acquired and installed. This will improve the current poor coverage by conventional weather stations. The coverage could also be improved by installing mobile weather sensors, which could be mounted on mobile objects such as long distance buses that travel to the cities from remote villages. The latter requires careful design work involving both computer scientists and meteorologists. Secondly, the capture of the IK into the system will be improved by acquiring additional android phones to run the IK data capture application. Thirdly, longitudinal studies of the use of the indigenous mobile phone application based on the Mbeere and Abanyole communities (and any other community) for period of about three years would go a long way in enriching the DEWS. Availability of the latter together with localised weather data from the sensors would also provide adequate dataset to run meaningful integrated drought forecasts.

Drought Monitoring and Predicting component, some work into how the output from the ANNs could automatically be integrated as input into the IK fuzzy logic sub-system is required. Since both sub-systems are currently implemented using MATLAB Toolboxes, this integration is feasible. Once this is done, learning ability needs to be integrated into the resulting sub-system. One way of achieving this is adoption of BDI agents' model that supports learning.

On the ability of EDI to map droughts in absolute terms; we recommend that data from other stations in other regions (in Kenya and beyond) be used to analyse historical droughts. With these results, our ANNs models can then be used to forecast droughts for different lead-times. Under this, it would be interesting to find out why the forecasting models performance degrades (to below 70%) after 4 year lead-time. Other ANNs models could also be experimented on using by altering various aspects of ANNs design such as dataset division criteria, data pre-processing and determination of model input. The latter is especially important because it will help determine if the decisions we made in combining AWRI, EDI and P apply across regions. Further, some aspects of drought monitoring and prediction could be decentralised and executed on mobile phones. One way of achieving this is to write some routines that can be executed on the android phones currently running the indigenous knowledge drought data collection application. This could be implemented as a service on our MobiGrid.

Drought Dissemination and Communication; innovative enhancements will be required in order to make the system more accessible, usable and relevant to the semi-illiterate small-scale farmers whose only access to ICTs is via mobile phones that are mostly low-end. The current format of the forecasts is still rigid and improvements on this are needed to improve the system's usability. Secondly, on the overall 'look-and-feel' of the integrated system, some improvements are needed especially in the way the information is displayed on the website. Use of Google maps to visually display drought levels and web-interface to the MATLAB Toolboxes (ANNs and Fuzzy Logic) will help in making the system user-friendlier.

Institutionalisation: Before the output from the DEWS is made public, the system prototype needs to be anchored into a formal institution that will be responsible for the fourth component of the DEWS; 'Response Capability'. Such an institution should put necessary measures in place before/after issuing alerts such 'looming drought'. It will also take liability for any consequences arising from the forecasts/alerts issued. The robust indigenous drought coping and mitigation strategies of the local communities should also be anchored on this institution. This will promote sharing and conservation of this valuable aspect of indigenous knowledge on droughts. Finally, apart from securing all the resources needed to roll out the DEWS, this institution should acquire the necessary registrations that are needed before recognition (such as acquiring ICAO identities) of new weather stations by WMO. This is especially so for the stand-alone sensor-based stations that must first be registered before their readings are used.

IKFs Longitudinal Studies: with the help of ITIKI, we further recommend IKFs longitudinal studies running for at least 3 years be carried out. Mbeere and Bunyore in Kenya are ideal candidates for this. These studies will enable collection of adequate data(especially IK) to further validate some of our findings.

Sensor Board Technical Issues that need to be resolved include battery power management and instability of the GPRS module. Even with well-written program code (like sending the boards to sleepmode when not in use), the batteries get depleted after about 7 days. Though this is currently handled by having multiple batteries to replace the depleted ones, a more sustainable solution around solar power that is readily available in most SSA countries should be pursued. On the other hand, the biggest bottleneck to the sensors' operation is the GPRS module that frequently fails and cuts-off the communication between the sensors and the DEWS. A solution that makes use of the Waspmote's Gateway (uses XBee Radio and XBee Antennas) could hold a key to solving this problem. Further, the sensor boards were not completely ready for use in the field; they needed an enclosure to protect them from things such as rain and direct sun light. This should be designed with the input of meteorologists to ensure that various meteorological WMO recommended specifications are met.

Subjective accuracy of sensor boards versus manual weather stations: the very nature of sensors and observation methods of their readings poses some challenges and questions for meteorologists. Unlike manual weather stations that are commonly used in SSA, the operation of sensors-based weather stations is highly automated; for instance, readings can be taken and stored in a database at a very high frequency (seconds) if need be. The challenge here is that in determining the 'best' reading for a given hour (say 6 GMT), is it better to just report the reading taken at 5:59 GMT or the cumulative readings taken throughout the hour? Further, the weather station readings used to carry out the calibration work discussed in this thesis were those from a manual weather station. A human operator does recording of the readings from these stations and therefore chances of errors may not be ruled out. Further experiments to compare the sensor readings with values read from automatic weather stations are recommended.

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11. Appendices

Appendix 11-1 – Sample Seasonal Climate Forecast

REPUBLIC OF KENYA

MINISTRY OF ENVIRONMENT AND MINERAL RESOURCES
KENYA METEOROLOGICAL DEPARTMENT
Dagoretti Corner, Ngong Road, P. O. Box 30259, Nairobi, Kenya,
Telephone: 254-20-3867880-5, Fax: 254-20-3876955/387373,
E-mail:director@meteo.go.ke

PRESS RELEASE

THE OUTLOOK FOR THE MARCH-APRIL-MAY (MAM) 2012 "LONG-RAINS" SEASON IN KENYA

Ref No: KMD/FCST/5-2012/SO/01

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1. HIGHLIGHTS

- *Depressed and poorly distributed rainfall is expected over most parts of the country during March-May 2012 "Long-Rains" Season.*
- *The western counties and the northern Coastal strip are likely to experience slightly enhanced rainfall while several places in Northeastern Kenya are likely to experience highly depressed rainfall.*
- *Most of the rainfall in various parts of the country is still expected during the peak month of April.*
- *Weak **La- Niña** conditions (cooler than average sea surface temperatures (SSTs)) are still present over the eastern and central equatorial Pacific Ocean. Slightly cooler than average SSTs were also observed over western Equatorial Indian Ocean during January and February 2012.*
- *Warm SSTs over the South-west Indian Ocean basin are conducive for the formation of Tropical Cyclones (TCs) during the March to May period. The TC presence over Malagasy and Mozambique Channel have a tendency to divert rainfall – bearing winds from the country and cause dry spells. The TC presence may, therefore, affect the forecasted rainfall conditions over different parts of the country. The TC season spans from 15th November to 30th April of the following year. During the current 2011-12 TC season, three named TCs and six Tropical Storms have so far been reported.*

2. FORECAST FOR MARCH-APRIL-MAY (MAM) 2012 "LONG-RAINS" SEASON

March to May constitutes an important rainfall season over Kenya and much of East Africa in general. The highest rainfall amounts recorded over Western, Central and Southeastern Kenya is over 250mm ***(Figure 1).***

The forecast for March-April-May (MAM) 2012 is based on the prevailing and expected Sea Surface Temperature Anomalies (SSTAs) over the Pacific, Indian and Atlantic Oceans as well as other large scale (Synoptic), Small scale (Mesoscale) and local factors that affect the climate over Kenya. These factors were assessed using various tools including: ocean-atmosphere models; statistical models; satellite derived information; and expert interpretation.

The prevailing weak La-Niña conditions over eastern and central equatorial Pacific Ocean and the cool Sea Surface Temperatures (SSTs) in the western Equatorial Indian Ocean were also taken into consideration.

The predicted Onsets, Cessation and Distribution of rainfall over the country were derived from statistical analysis of past years, which exhibited similar (analogous) characteristics to the current year.

The forecast for MAM 2012 "Long Rains" Season indicates that most parts of Kenya are likely to experience near-normal rainfall with a tendency towards below-normal (i.e. depressed rainfall). However, the western areas and a few areas along the Northern Coastal strip are likely to experience near-normal rainfall with a slight tendency towards above-normal (i.e. slightly enhanced rainfall) ***(See Figure 2)***.

The specific outlook for MAM 2012 'Long Rains" Season indicate that:

i. ***Western Counties*** (Busia, Butere, Mumias, Vihiga, Kakamega, Bungoma, etc.); ***Nyanza Counties (***Kisumu,Siaya, Migori, Kisii, Kuria, Nyamira, Borabu, Gucha,etc**); Counties in the central and Southern *Rift Valley*** (Trans Nzoia, Uasin Gishu, Kericho, Nandi, Nakuru, Narok, Kajiado, etc); **Northern *Coast Province*** (Lamu, Mpeketoni etc) will receive Near-Normal rainfall with a slight tendency towards Above-Normal (i.e. slightly enhanced rainfall).

ii. ***The Central Counties*** (Nyandarua, Nyeri, Kiambu, Murang'a, Kirinyaga, etc.**); *Nairobi County*** (Westlands, Embakasi, Kasarani, Dagoretti, etc); **Most Counties in Eastern Province** (Embu, Meru, Mwingi, Machakos, Makueni, Makindu, Marsabit, North Horr etc); **Most Counties *in Coast Province*** (Malindi, Kilifi, Voi, Mombasa, Tana River, Kwale, Msambweni, Kinango, Lungalunga etc); **Most Counties in Northern *Rift Valley*** (Turkana, Pokot, etc); **Parts of Northeastern** (Garissa, etc.) will receive Near-Normal rainfall with a tendency towards Below-Normal (i.e. slightly depressed rainfall).

iii. **Most Counties in Northeastern** (Mandera, Ijara, Wajir, Elwak); **Some Counties in Eastern Province** (Moyale etc.) will receive below normal (i.e. highly depressed) rainfall.

3. EXPECTED SEASONAL RAINFALL DISTRIBUTION

The March to May 2012 "Long-Rains" are likely to exhibit poor distribution, both in time and space, over most parts of the country and more so in the Arid and Semi-Arid Lands (ASALs) ***(See Figure 3a and 3b).***

- In northwestern Kenya (Turkana, Pokot, etc), the rainfall performance is likely to be depressed in March and May but slightly enhanced in April.
- Enhanced rainfall is expected over the western highlands, Lake Basin and central Rift Valley in March and April. It is, however, expected to be depressed in May.
- The central highlands including Nairobi area are expected to receive depressed rainfall in March and April and near-average rainfall in May.
- The northeastern districts are likely to experience depressed rainfall throughout the season.
- The southeastern districts are expected to receive enhanced rainfall in April but depressed rainfall in March and May.
- The performance along the Coastal Strip is expected to be Near-Normal in May but depressed in March and April.

4. EXPECTED ONSET AND CESSATION DATES

	Region	Onset Dates	Cessation Dates
1	Counties in the Lake Basin (Western and Nyanza) and in Highlands West of the Rift Valley	The rains will be enhanced from 2nd to 3rd week of March 2012	Continue into June
2	Southern parts of the Rift Valley	The rains will be enhanced from 2nd to 3rd week of March 2012	3rd to 4th week of May 2012
3	Central Rift Valley	2nd to 3rd week of March 2012	Continue into June
4	Central highlands including Nairobi	3rd to 4th week of March	3rd to 4th week of

	area	2012	May 2012
5	South eastern Counties	3rd to 4th week of March 2012	1st to 2nd week of May 2012
6	Coastal Strip	4th week of March to 1st week of April 2012	Continues into June 2012
7	North-eastern and North-western districts	4th week March to 1st week April 2012	1st to 2nd week May 2012

The expected Onset and Cessation dates are also shown in **Figures 3a and 3b,** respectively.

5. POTENTIAL IMPACTS

5.1 Agriculture and Food Security Sector

In the agricultural counties of Western, Nyanza and Rift Valley where rainfall is expected to be Near-Normal with a tendency towards Above-Normal, the farming communities should take advantage of the rains and maximize crop yield through appropriate land-use management. Farmers are advised to work closely with the Ministry of Agriculture on ways of taking advantage of the expected good rainfall.

In other agricultural counties within the Central, Southeastern and Coastal Kenya, where the rainfall is expected to be Near-Normal with a tendency towards Below-Normal, farmers are also advised to liaise with the Ministry of Agriculture to get advice for the best use of the rains by planting appropriate crops.

5.2 Disaster Management Sector

Lightning strikes may occur in western Kenya especially within Gusii and Kakamega counties owing to strong convective activities between Lake Victoria, Mau Escarpment and Mt. Elgon. Budalang'i and Kano areas are also likely to experience some degree of flash flooding while isolated cases of landslides/mudslides are still probable in some parts of Western and Rift Valley. The National Disaster Operations Centre is, therefore, advised to take the necessary measures that would ensure mitigation of any negative impacts resulting from the forecast conditions.

5.3 Energy Sector

The Turkwel and Sondu Miriu catchment areas are expected to experience Near-Normal rainfall with a slight tendency to Above-Normal during the coming season (March-May). It is, therefore, expected that the level of water in the hydroelectric power generation dams will improve significantly during the season. The Normal to Below-Normal rainfall expected in Tana River catchment areas is, however, likely to lead to low water inflows into the Seven-Folks hydroelectric power generation dams.

5.4 Transport and Public Safety

Flash floods may still be experienced especially in Western and some parts of Central Kenya. This may lead to transport problems, especially during rush hours and more so in areas where the roads become impassable when it rains. Slippery roads and visibility during rainstorms may also pose dangers to motorists and pedestrians. All should, therefore, take utmost care during the rainy period.

Light aircrafts are advised to take utmost care in the western routes and avoid flying through deep cumulus clouds, especially in the afternoon hours. Such clouds are associated with severe turbulence (very strong updrafts and downdrafts of air and cross-winds occasioned by strong convections) and lightning.

5.5 Water Resources Management Sector

Water resources for drinking, sanitation and industrial use in most municipalities of the country are expected to be minimal due to the expected depressed rainfall. The currently available water should, therefore, be well managed especially over areas forecasted to get deficient rainfall. This should be more so in the marginal areas in order to cater for the animal and human population needs.

5.6 Local Authorities

Municipalities located in regions expected to experience Near-Normal rainfall with a tendency to Above-Normal are advised to open up drainage systems early enough to avoid water accumulation due to surface runoff which could lead to flash flooding. The Municipalities are also encouraged to develop capacities that cater for an ever-increasing population, due to increased rural-urban migration.

5.7 Health Sector

Water-borne diseases associated with poor sanitation, like cholera and typhoid, as well as flooding may emerge in areas expected to receive enhanced rainfall. Health authorities are, therefore, expected to be on the look out and equip hospitals with necessary drugs to be able to deal with such situations as they arise. There is also need to be on the lookout for Highland Malaria in regions that are expected to receive enhanced rainfall.

5.8 Trade and Industry

In areas expecting slightly enhanced rainfall, some sections of the road network may be muddy and slippery. Vehicles may stall in the muddy sections. This scenario is likely to result in late delivery or non-delivery of raw materials and industrial products to the industries and distribution outlets to commodity markets respectively and affect commerce.

5.9 Environment

In areas expected to receive enhanced rainfall, the Ministry of Environment and Mineral Resources should encourage residents in these areas to put in place soil conservation measures to minimize environmental degradation due to soil erosion by surface run-off of rain water. People should also be encouraged to plant more indigenous trees in order to increase forest cover to the internationally agreed target of 10% of forest cover over the country.

6. WEATHER REVIEW

6.1 PERFORMANCE OF THE OCTOBER-NOVEMBER-DECEMBER (OND) 2011 "SHORT RAINS" SEASON

Analysis of the "Short Rains" (October-November-December) 2011 seasonal rainfall indicates that the performance was generally good over the entire country. All the meteorological stations in the country recorded at least near normal (above 75% of the Long-Term Mean (LTM)) rainfall. Indeed, several stations recorded highly enhanced rainfall that led to serious flooding and destruction of infrastructure in various counties. Wajir, Lodwar and Mandera Meteorological Stations, for example, recorded more than 300 percent of their seasonal LTMs while Lamu, Msabaha, Marsabit, Narok and Malindi Meteorological Stations recorded amounts in excess of 200 percent. All the other meteorological stations in the country except Garissa, Thika, Mombasa, Embu, Machakos and Makindu, also recorded above normal (>125% of their LTMs) rainfall. Embu, Machakos and Makindu were the only stations in the country that did not attain 100 percent of their seasonal LTMs.

The highest seasonal rainfall amount of 1034.1mm (150%) was recorded at Meru Meteorological Station while Kisii, Marsabit, Kericho, Kakamega, Embu and Wajir Meteorological Stations recorded 741.7mm (138%), 725.4mm (245%), 616.1mm (153%), 574.2mm (145%), 513.5mm (96%) and 508.0mm (365%) respectively. Msabaha, Kisumu, Nyeri, Voi, Wilson Airport, Moyale, Narok, Dagoretti Corner and Kitale Meteorological Stations recorded between 400 and 500mm. The rest of the Meteorological Stations recorded less than 400mm. The lowest seasonal rainfall percentage of 84% was recorded at Makindu Meteorological Station in the South-eastern lowlands of Kenya (**see figures 4a and 4b**).

6.2 OBSERVED CONDITIONS DURING JANUARY-FEBRUARY 2012

Sunny and dry weather conditions prevailed over the entire country, including the western areas, during the two months (January-February) period. Consequently, most meteorological stations recorded higher than average daytime (maximum) temperatures. Some of the temperatures were the highest recorded in the last thirteen years (since 2000).

In January 2012, most stations in the country except Nyeri and Meru, recorded nil or very low monthly rainfall amounts. The stations that recorded some rainfall had monthly totals of less than 10mm. The highest rainfall recorded in January occurred in the central Highlands where Nyeri station recorded the highest monthly rainfall total of 56.6mm. Meru station recorded 12.1mm while the rest of the stations recorded less than 10mm or no rainfall at all.

In February, Kisii station in western Kenya recorded the highest rainfall amount of 69.3mm while Narok, Kisumu, Nakuru, Nyahururu, Kakamega and Thika stations recorded 60.6, 43.4, 33.6, 29.8, 21.0 and 20.9 mm respectively. The rest of the stations recorded less than 20 mm.

7. EXPERIENCED IMPACTS

7.1 OND 2011

The enhanced rainfall during the OND 2011 season was associated with both positive and negative impacts.

Positive impacts

- Good crop performance over most of the central highlands and parts of southeastern Kenya.
- Improved foliage and pasture for the pastoralists in the pastoral areas of Northwestern and Northeastern Kenya.
- Increased water levels in the Seven-Folks and Turkwel hydroelectric power generation dams.
- Improved food security in various parts of the country.
- Increased water resources for domestic use (drinking and sanitation, etc.) as well as industrial use in all parts of the country and in particular the counties in Northern, Northeastern and Southeastern parts of the country that were water stressed during the previous seasons.

Negative impacts

- Several families, especially in western Kenya, were displaced from their homes following the heavy rainfall that caused serious flooding in the flood-prone areas of Bundalang'i and Nyando.
- The heavy rains also led to destruction of infrastructure whereby several roads were rendered impassable in different parts of the country.
- A few people lost their lives and several animals were swept away by raging flood waters
- The heavy rains that occurred in November disrupted Standard Eight exams in parts of Rift Valley, Nyanza and Coast provinces.
- Heavy rains triggered landslides in Elgeyo Marakwet, Baringo and Murang'a Counties. As a result, about 50,000 families were affected.
- In Nairobi, heavy rains paralyzed traffic in the City on various occasions. Several motorists stalled overnight in the flooded streets. The heavy rains also led to power blackouts in various parts of Nairobi as power posts that support transformers fell down.

7.2 JANUARY – FEBRUARY 2012

The sunny and dry weather conditions over various parts of the country continued to impact negatively on various sectors. The negative impacts included:

- Deterioration of pasture and shortage of water for animals in the pastoral areas;

- Commencement of a gradual decline in the the water levels in the hydro-electric power generating dams;
- Cases of wild fires were reported over various parts of the country. This was as a result of the sunny and dry conditions together with strong winds that provide very conducive conditions for wild fires.
- Frost formation that affected tea, potatoes and even bananas occurred in some of the highland areas including parts of the Mau Escarpment and the Aberdare ranges.

NB: This outlook should be used with 24 hour forecasts and regular updates issued by this Department.

Dr. Joseph R. Mukabana, MBS
DIRECTOR OF METEOROLOGICAL SERVICES & PERMANENT REPRESENTATIVE OF KENYA WITH WMO

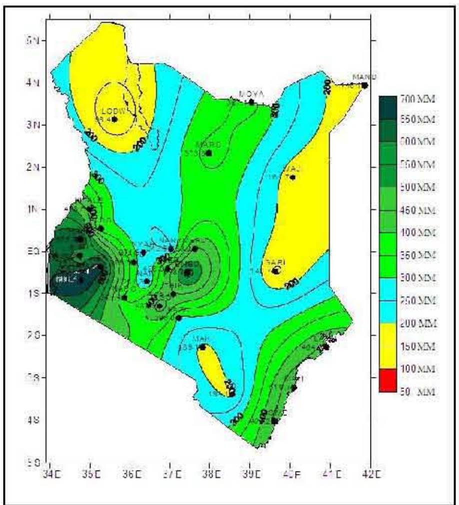


Fig. 1: Mean Rainfall in March-May (Normal)

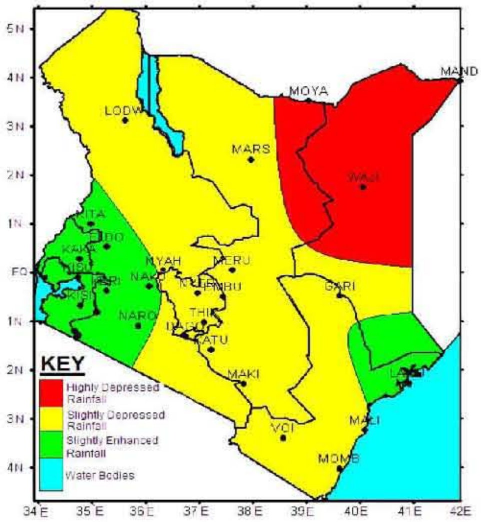
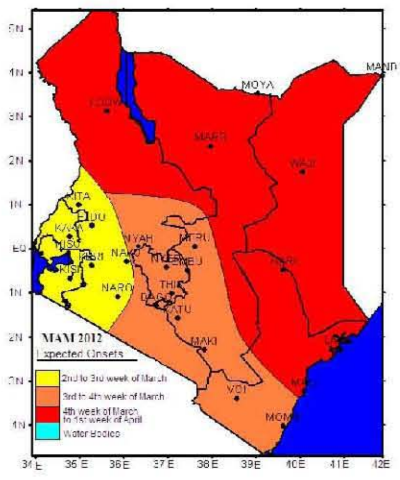
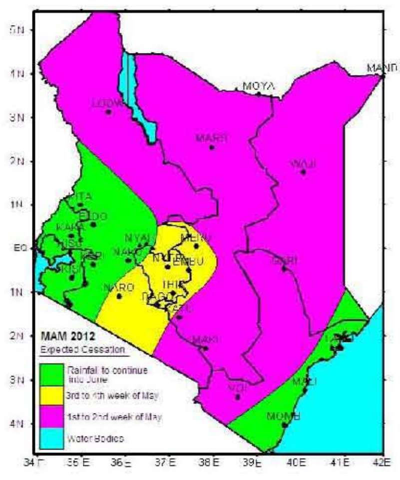


FIG. 2: MARCH-MAY (MAM) 2012 SEASONAL RAINFALL (FORECAST)





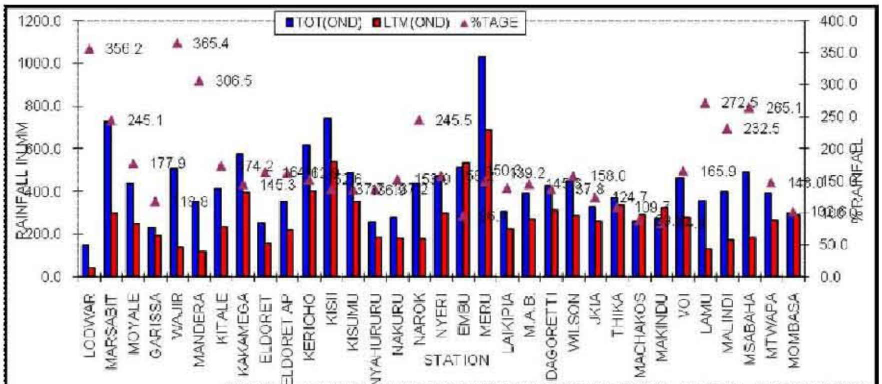


FIGURE 1: OCTOBER-NOVEMBER-DECEMBER 2011 SEASONAL RAINFALL PERFORMANCE

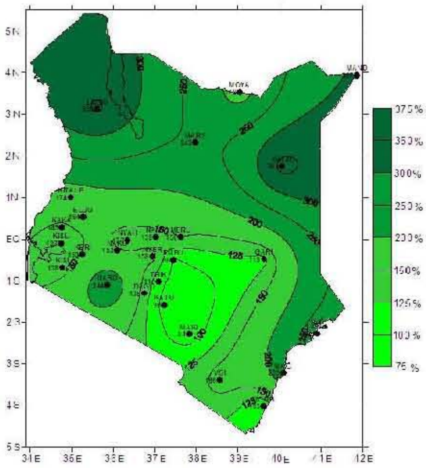


FIGURE 4B: OCTOBER-NOVEMBER-DECEMBER (OND) 2011 RAINFALL DISTRIBUTION IN KENYA (ACTUAL)

Appendix 11-3: 14th Dekad, 10 to 20 May 2009

AGROMETEOROLOGICAL BULLETIN
KENYA METEOROLOGICAL DEPARTMENT

KMD

14th Dekad, 10 to 20 May 2009

HIGHLIGHTS

Issue No 14/2009 Season: AMJ

During the 13th Dekad i.e. 11th - 20th May 2009, most parts of the country experienced some rainfall. Moderate to heavy rainfall was experienced over western and Nyanza Provinces and Central Rift Valley, with Kakamega, Kisii, Kisumu, Kericho, Kitale, Eldoret, Nakuru and Narok recording 121.7, 70.6, 184.5, 81.8, 68.6, 140.1, 144.0, and 83.8 mm respectively. Central Province, areas bordering Mt Kenya, Nairobi Area and its environs experienced moderate rainfall with the following Dekadal totals; Nyeri-90.8mm, Embu-38.6mm, Meru-51.7mm, Mwea- 70.2, Thika- 26.9, Dagoretti-66.5mm and Kabete-35.3mm. The Southeastern Lowlands of Eastern Province experienced insignificant light rainfall with Katumani recording a Dekadal rainfall total of 3.5. The Coastal region experienced moderate to heavy rainfall with Mombasa, Mtwapa, Mshabaha, Malindi and Lamu recording, 52.6, 127.5, 140.6, 107.4and 97mm respectively. North-eastern Province and North-western Districts, except for Moyale which recorded the highest Dekadal rainfall of 80.0 mm, the rest experienced mainly sunny conditions and light rainfall over few places with Mandera, Wajir, and Lodwar recorded a Dekadal total of 6.6, 10.4, and 30mm respectively. Fig 1)

The current Long Rains has brought about improvements in both fodder for animals and hence an increase in milk production and also availability of fresh vegetables to many households.

Day time temperatures were relatively lower due to increased cloud cover over most parts of the country, with Lodwar, Mandera, Wajir, Garissa, Kakamega, Kisumu, Mwea, Makindu, Dagoretti and Mombasa recording a Dekadal Mean day Maximum of, 34.4, 36.4, 35.0, 35.0, 26.1, 28.1, 27.8 30.6, 23.6 and 30.1 deg Celsius respectively. Fig1, 2, 3.)

Night temperatures were relatively warm over most parts of the country due also to increase in cloud cover during the Dekad with Nyahururu, Narok, and Eldoret Airport recording a Dekadal mean minimum of 9.6, 14.2, and 11.8 deg Celsius respectively. Fig1, 2&3).

The pastoral regions and game parks of Southern Rift Valley, North Eastern, South Eastern Lowlands and the Coastal regions, experienced moderate to heavy rainfall which was a relief to water sources for both human and animal use. Despite the rains pasture regeneration and animals health conditions is gradually improving. Figs. 1- 3)

The acute famine and hunger and the associated impacts previously experienced in many parts of the Country especially in Eastern, Central, Coast, North-eastern, Nyanza and Northern and Southern Rift Valley Provinces are gradually getting eroded with time, due to improvement in both food and milk availability. Figs. 1- 4).

CROP AND WEATHER REVIEW
11th to 20th May 2009)

Central Province and Nairobi Area:
Moderate to heavy rainfall was experienced over most places in Central province, Nairobi area and its environs during the Dekad enhancing the soil moisture status. Generally most crops cash and food crops) are doing well and corresponding to normal growth. Weeding and topdressing is taking place but, has been completed in most places. The maise crop is at emergence stages, while the bean crop is at the flowering stage and both are doing well. Figs.1-4).

Eastern Province:
Moderate rainfall was experienced over most places bordering Mt. Kenya Embu, Runyenjes, Chogoria, Chuka and Meru) during the Dekad sustaining the soil moisture status. Most crops cash and food crops) are doing well and corresponding to normal growth. Weeding and topdressing is taking place but has been completed in most places. The maise crop is at emergence stages, while the bean crop is at the flowering stage and both are doing well. Figs.1-3).

In the Southern Lowlands of the Eastern Province Machakos, Makueni, Mwingi and Kitui districts),sunny conditions with light rainfall was experienced over most places during the Dekad. The maise and beans crops planted late or re-planted are at emergence and flowering stages respectively are doing well and corresponding to normal growth. Weeding and topdressing is taking place in most places.

Coast Province:
Heavy rainfall was experienced over several places during the Dekad Lamu, Malindi, Kwale and Voi). Late planted maise and beans crops are at emergence stages and are doing well and corresponding to normal growth. Weeding and topdressing is taking place in most places.   Figs.1-3)

North Eastern Province:
Sunny and dry conditions dominated the region Mandera, Moyale, Wajir and Garissa) during the Dekad, with light rains being reported over few places. There was a sigh of relief to water sources for livestock, wildlife and human use. Despite the light rains pastures regeneration and the animals health conditions remained generally poor, due to the recent severe drought. Figs.1, 2, 3 & 4)

Famine/hunger is still being experienced in most places.

Western Province:
Moderate to heavy rainfall were experienced over over most places of this region Kakamega, Bungoma, Busia) during the Dekad. Generally most crops cash and food crops) are doing well and corresponding to normal growth. Weeding and topdressing is taking place. The maise crop is at emergence stages, while the bean crop is at the flowering stage and both are doing well. The only adverse effects reported on crops was insufficient rainfall and crops are wilting areas around Eldoret Kapsoya).   Figs.1-3).

Nyanza and Central Rift Valley:
Moderate to heavy rainfall were experienced over several places in this regions Kisumu, Nyamira, Kisii, Eldoret, Kitale, Kericho) during the Dekad. Most crops cash and food crops) are doing well and corresponding to normal growth. Weeding and topdressing has taken place in most areas. The maise, bean and sorghum are at the flowering stages and are doing well and corresponding to normal growth with normal yields being expected.

In areas around Kisii maise and bean crops are at the flowering and maturity stages respectively and are doing well and corresponding to normal growth with normal yields being expected.

The only adverse effects reported on crops around Eldoret Kapsoya) was insufficient rainfall in the initial stages and crops which survived are stunted with poor yields being expected. Figs 1-4)

Northern and Southern Rift Valley:

Northerwestern Rift Valley Lodwar, Lokitang) experienced generally sunny and dry conditionswith light rains over few places during the Dekad. This has resulted in poor pastures regeneration and inadequate water sources for livestock, wildlife and human use leading to death of livestock and wildlife. Figs.1-4).

Famine/hunger and its related impacts is still being experienced and malnutrition levels are still high

Southern Rift Valley Narok, Kajiado, Mara) experinced light to moderate rainfall, which was a sigh of relief to water sources for livestock, wildlife and human use. In the pastoral areas pastures regeneration and animals health are gradually improving.

For the farming community, most crops cash and food crops) are doing well and corresponding to normal growth. Wheat, maise and bean crops are at the emergence stages and are doing well and corresponding to normal growth weeding and top dressing is taking place.

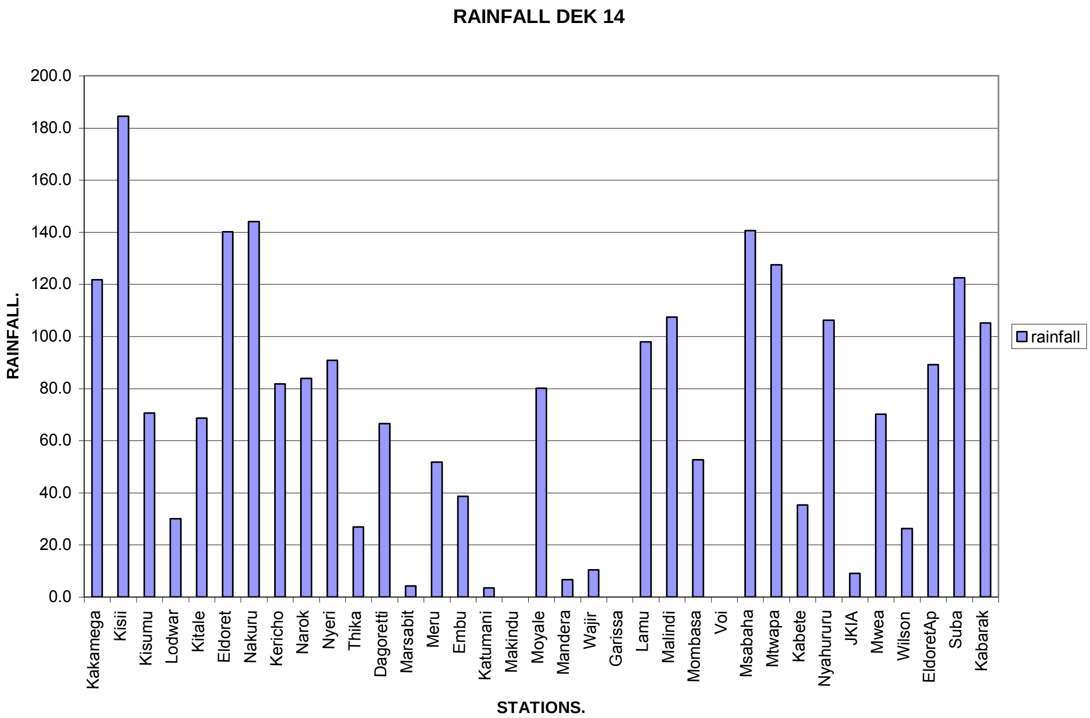


Fig. 1: Actual Rainfall 11th to 20th May, 2009) in mm

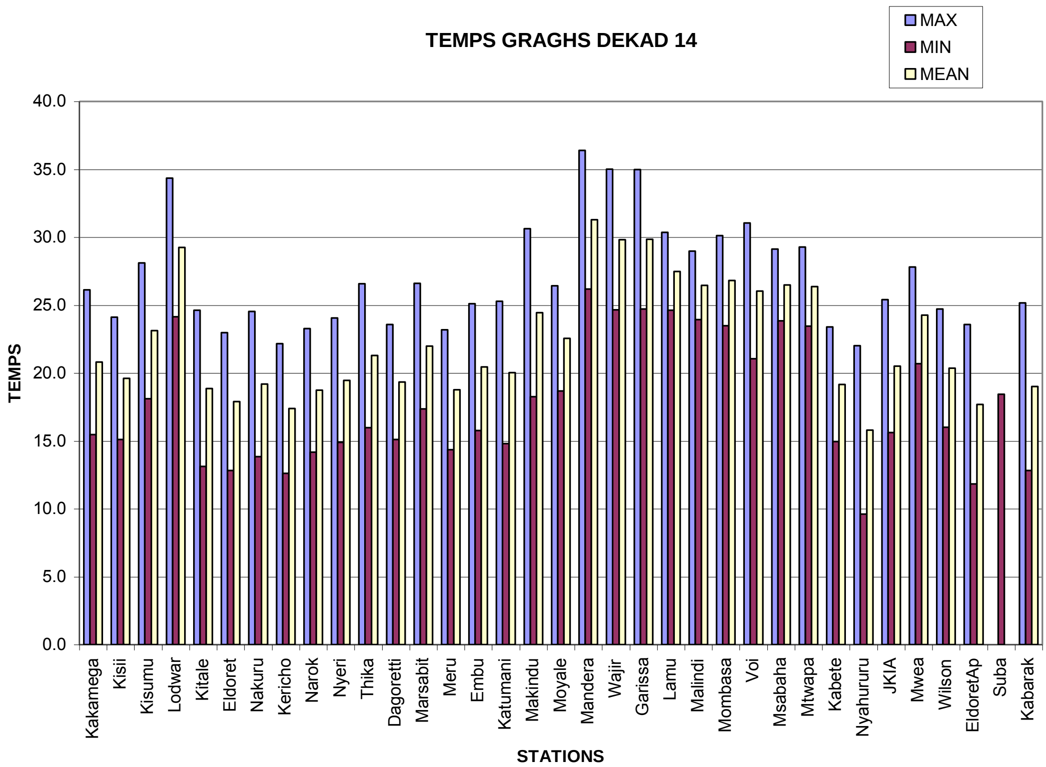


Fig 2: Mean Temperatures 11th to 20th May, 2009) deg. Celsius

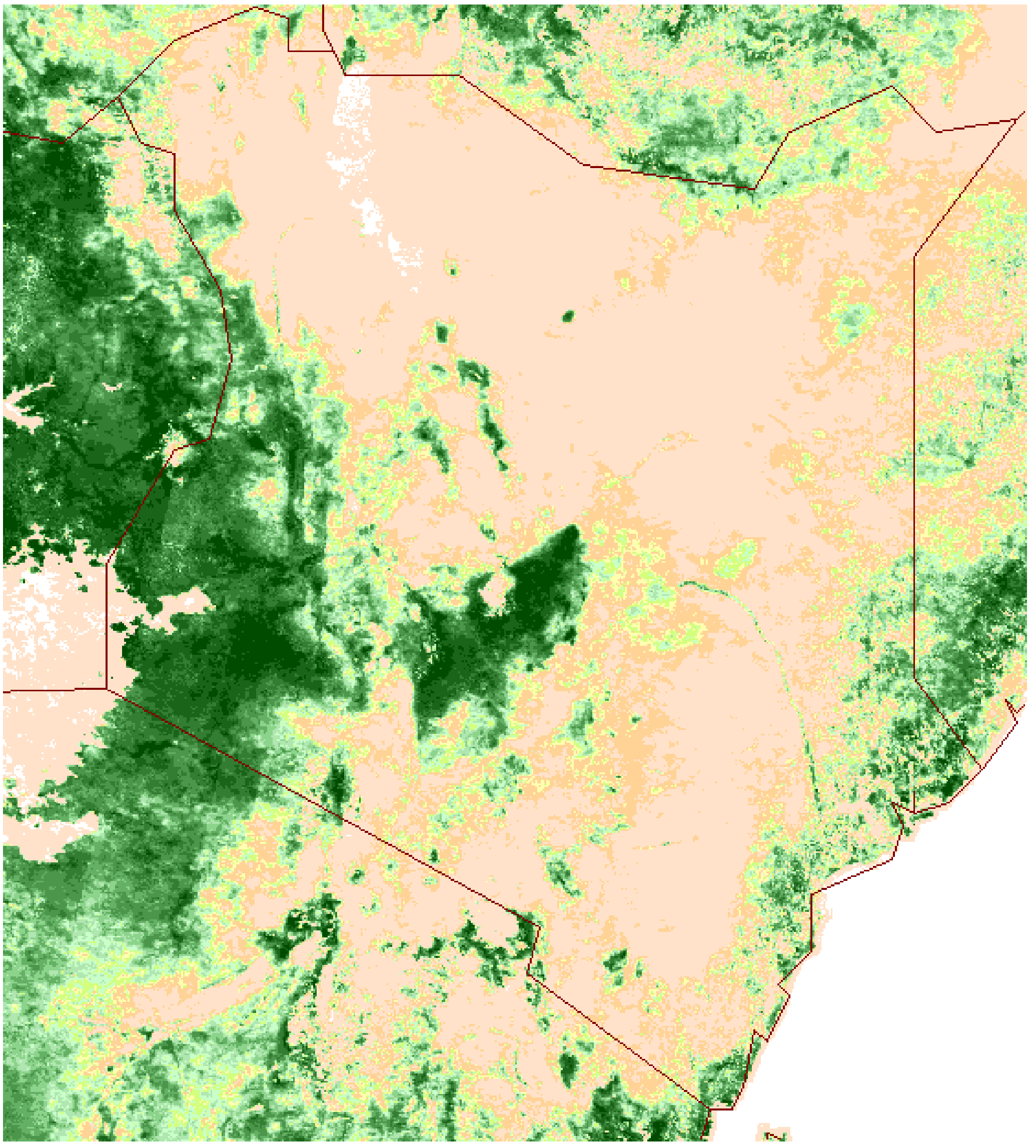


Fig. 3: Dekad 14 Normalised Difference Vegetation Index **(11 to 20 May 2009)**

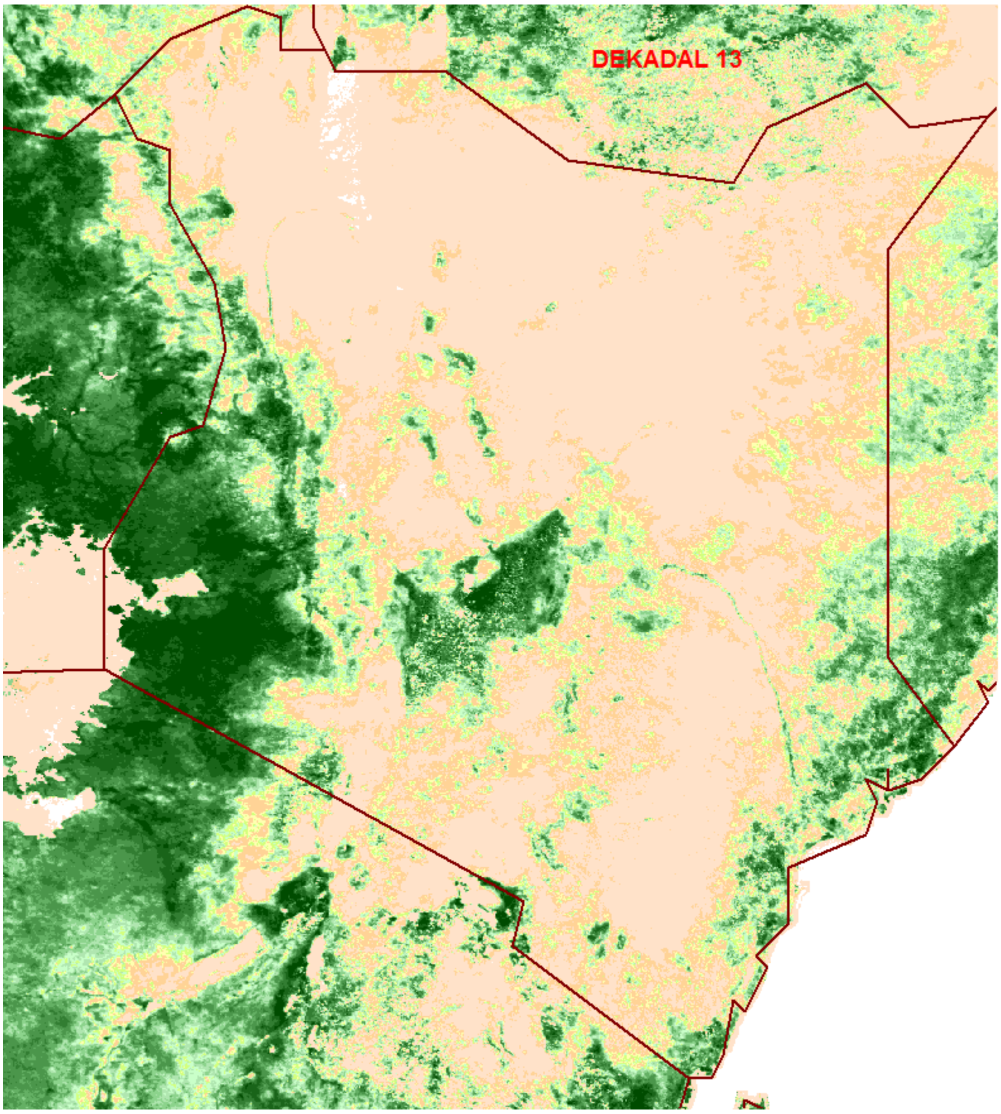


Fig. 4: Dekad 13 Normalised Difference Vegetation Index **(1 to 10 May 2009)**

EXPECTED WEATHER AND CROP CONDITIONS DURING THE NEXT 10 DAYS 21st – 31st May 2009).

During the next 10 days 21st – 31st May) Western, Nyanza and Central Rift Valley regions are expected to experience moderate to heavy rainfall over several places and crops are expected to continue doing well and correspond to normal growth with normal yields being expected. However, excessive rainfall may cause damage to crops especially in the low lying areas, due to water logging.

Central Highlands, Nairobi area and its environs, are expected to experience moderate to heavy rainfall over several places and crops are expected to continue doing well and correspond to normal growth. The beans is expected to reach the maturity stages and with normal yields being expected.

In Eastern Province regions of Embu and Meru districts, bordering Mt Kenya, are expected to experience moderate to heavy rainfall in several places and crops are expected to continue doing well and correspond to normal growth. The beans is expected to reach the maturity stages and with normal yields being expected.

In South-Eastern lowlands, generally sunny conditions with light rains over few places are expected. Poor crop performances are expected due to insufficint rainfall during past Dekad.

The Coastal region is expected to experience moderate to heavy rainfall during the Dekad. Poor crop performance is are expected due to insufficint rainfall during early stages.

In the pastoral regions and game parks/reserve of North-western, North-eastern, Northern Rift Valley districts sunny and dry conditions are expected to prevail, with light rainfall expected over few places. Inadequate pastures and water sources for human and animal/wildlife use are expected. Southern Rift Valley is expected to experience light to moderate rainfall which will boost the water sources and improve pastures regeneration and food production. Animal's health both livestock and game) is expected to gradually improve as the pastures conditions gradually improve.

In summary, wet conditions are expected over several places of the country during the next ten days. Crops are expected to continue doing well and correspond to normal growth in most regions of the country.
Despite the onset of the rainy season, drought impacts are expected to persist for a while and famine relief efforts expected to continue in the affected areas.

This product should be used in conjunction with Kenya Meteorological Department weather forecasts. For more information, Contact

The Kenya Meteorological Department
Agrometeorological Division
Dagoretti Corner, Ngong Road,
P.O. Box 30259, 00100 GPO, Nairobi
Tel: +254 0)20 3867880-7/3876957/3873682
Fax: +254 0)20 3876955
E-mail: agromet@meteo.go.ke
Website: www.meteo.go.ke

Appendix 11-3 – Estimated Cost of ITIKI Implementation

Overview

The salient features of ITIKI require that its implementation is people-driven (especially the small-scale farmers). As such, anchoring this within a local (to the implementation region/area) community based organisation, church, non-governmental organisation and so on is recommended. The Mbeere implementation pilot mentioned in this thesis was anchored within a Community Based Organisation. The estimated implementation cost below is therefore based on this fact.

Equipment Cost

The major cost is associated with the sensor boards; we used Agriculture and Agriculture PRO sensor boards from Libellium. In 2011, it would cost about 2,500 Euros to acquire a complete weather meters for measuring all the necessary weather parameters (including soil moisture) for an area of about 200km^2. At the time of writing this thesis, there were strong indicators that the cost of such meters was going down and the number of suppliers was going up. Below is a sample quotation issues in May 2011:

Libelium Comunicaciones Distribuidas S.L.
María de Luna 11, Nave 5
CEEI Aragon
50018 Zaragoza Zaragoza
Phone: +34 976547492
Fax: +34 976733719
CIF: ESB99135832

University of Nairobi
Muthoni Masinde
The School of Computing and Informatics,
Nairobi,
Kenya

Date Promised : 16/05/2011
Customer No : University of Nairobi
Representative Solobera Abad, Javier

Proforma Invoice Document No 23116 - 16/05/2011

ID	Description	Price	Qty	Line Amt
3110	Waspmote 802.15.4 SMA 2 DBI	135,00	5	675,00
6014	1150 mA·h Rechargeable Battery	19,00	5	95,00
3210	Waspmote Gateway 802.15.4 SMA 2 DBI	65,00	1	65,00
3046	Waspmote Agriculture board	130,00	4	520,00
3047	Waspmote Agriculture board PRO	250,00	1	250,00
9203	Temperature Sensor	3,00	5	15,00
9248	Watermark Soil Moisture Sensor	45,00	1	45,00
9204	Humidity Sensor	20,00	5	100,00
9250	Air Pressure Sensor	25,00	1	25,00
9256	Weather Meters	125,00	1	125,00
3040	GPS Waspmote Module	65,00	1	65,00
3041	GSM / GPRS Waspmote Module	85,00	1	85,00
9240	Horizontal Liquid Level Sensor	20,00	2	40,00
	Bank Charges Libelium	20,00	1	20,00
	Shipping Libelium	269,00	1	269,00
	Exportacion 0%	2.394,00		0,00
Suma				***2.394,00***

EUR 2.394,00
Transference (pre-payment)
Bank Name: Ibercaja
IBAN: ES31 2085 0180 3603 3027 2372
Swift: CAZRES2Z

All prices are in EUR currency
Incoterm: EXW
Terms & Conditions: http://www.libelium.com/legal

Given the critical role of precipitation in ITIKI, we also recommend that the density of the weather meters be increased using about 10 conventional (manual) rain gauges for the area covered by the sensors boards. Other equipment costs were associated with android phone; about5 phones (at 80 Euros each). Finally, a computer server and an internet modem (to receive sensor readings and drought forecasts input/output) cost us about 500 Euros.

Recurring Cost

Most of the recurring cost is associated with the airtime for the mobile phones and the modem. A larger part of the cost in our case though emanated from some allowances (5 Euros per person per session or day) paid to the focus group members whenever they met to report/discuss IK indicators. We also contracted services of a Coordinator and Administrator to assist with the logistics on the ground. Below is a sample budget that we used for the Mbeere implementation

Sample Budget

A. Recurrent Expenditure:				
No Of Months	3			
Weeks Per Month	4			
1. **Allowances**				
	Unit Cost	**Unit (people)**	**Meetings Per Week**	**Total**
(a) Coordinator	2,000	1	2	48,000
(b) Administrator	1,000	1	2	24,000
(c) Focus Group	500	12	1	72,000
Sub-Total				**144,000**
2. **Consumables**				
(a) Airtime	500	1	1	6,000
(b) Stationery	250	1	1	3,000
(c) Miscellaneous	250	1	1	3,000
Sub-Total				**12,000**

B. Fixed Cost				
(a) Rain Gauges and Casing	-	5		0
(b) Android Mobile Phone	8,000	5		40,000
(c) Mini Laptop	30,000	1		30,000
(d) Printer	15,000	1		15,000
(e) Modem	2,000	1		2,000
Sub-Total				**87,000**
C. Stakeholders Workshop(Jan 2013)	2,000	30	1	**60,000**

Note: Cost is in Kenya Shillings (KES) – €1 ≈ KES 110 (October 2012)